Universidad Carlos III de Madrid

TESIS DOCTORAL

Essays on Occupational Choice, Intergenerational Persistence and Structural Change

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PROGRAMA DE DOCTORADO

Economia

Getafe, Abril 2018

uc3m | Universidad Carlos III de Madrid

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Leganés/Getafe, de de

Contents

Abstract

This doctoral dissertation consists of three chapters on different aspects of labor markets, especially related to occupational choice, intergenerational transmission and structural change. In the first chapter, I analyze how parents affect the occupational choice and employment prospects of offspring. In the second chapter, I study the determinants of occupational persistence across generations and its implication on the aggregate equilibrium and welfare. In the third chapter, I investigate how income inequality affects the relationship between structural change and growth.

In the first chapter, "*Parental Links and Employment Prospects: Evidence from the UK*" (joint with Iacopo Morchio), I study how parental links affect labor market choices and employment prospects of individuals, exploiting monthly job histories from the British Household Panel Survey (BHPS, hereafter). I document two important facts: i) occupational choice is correlated across generations; and ii) the offspring's job–finding probability is correlated to the father's employment, especially for those who find a job in their father's occupation. More specifically, I find that having an employed (rather than unemployed) father increases the employment rate by about 8 p.p. and the monthly job–finding rate by at least 50% (5–6 p.p.), whereas this does not hold for mothers. Furthermore, this correlation is much larger for younger workers. One potential explanation for this finding is that parental networks are an important source of information about job vacancies for workers. To illustrate this mechanism, I develop a stylized model of intergenerational transmission of networks in which agents with little or no experience in the labor market rely more heavily on parental connections, in line with my results. A number of robustness checks also suggest that the correlations that I find are indeed due to informational advantages rather then human capital transmission, direct hiring or common shocks.

In the second chapter, "*Like Father, Like Son: Occupational Choice, Intergenerational Persistence and Misallocation*" (joint with Iacopo Morchio), I study the determinants of oc-

cupational persistence across generations. The key contribution is to develop a framework with multiple sources of persistence and quantitatively assess their relative importance, in order to shed light on the relationship between persistence and misallocation. When the comparative advantage and the father's occupation (where contacts are available) are not perfectly aligned, some workers face a tradeoff between choosing the occupation in which they are most productive (higher wages) and the one in which they can exploit their father's network (higher job–finding rates). This implies that in equilibrium some workers will decide not to pursue their comparative advantage, generating *productive mismatch* in the economy, and thus producing negative externalities on firm entry. I test and confirm the key predictions of the model with panel data from the UK: occupational followers have, on average, finding rates (at the monthly frequency) which are at least 40% higher, implying that their unemployment spells are typically substantially shorter; also, I estimate a large wage discount, in the region of 7–14 log points. Next, I extend the theory to a dynamic quantitative model, that allows for preferences (non–pecuniary benefits for occupations) to be correlated across generations, and also for occupational mobility and accumulation/depreciation of human and social capital over the life–cycle. A persistence decomposition exercise suggests that the all transmission channels are relevant though by differing degrees, with the transmission of parental networks being the strongest force, able to account for about 79% of total persistence. When I shut down parental networks or the transmission of preferences, welfare improves, due to the improved (more aligned with productive advantages) allocation of workers to occupations: output per worker goes up, and firms react posting more vacancies per worker than before. Instead, when I shut down the transmission of abilities, the reduction in persistence is accompanied by a reduction in welfare, driven by the worse allocation of the workforce. Finally, the decomposition yields relevant implications for the evaluation of labor market policies such as unemployment benefits, and of the detrimental effects of search frictions on the sorting of workers.

In the third chapter, "*Structural Transformation, Innovation and Growth: the role of Income Distribution*", I document and rationalize a novel fact on structural transformation and growth. Working with a sample of 41 countries for the period 1960–2010, I show that outflows of labor from the agriculture sector are growth–enhancing only for economies with relatively low levels of inequality. A decrease of 10% in the agriculture employment share is associated with an increase in GDP per capita of 54.2% in low–inequality countries, while the predicted increase for high–inequality countries is only 23.5%. In other words, despite experiencing (even deep) structural transformations, several countries did not benefit much in terms of economic growth. Therefore, I develop a 2–sector endogenous growth model with a non–degenerate income distribution, which allows me to study the interaction of inequality, the employment shares and growth. In the model, income distribution shapes aggregate demand, which in turn: i) shapes the employment structure of the economy; and ii) generates incentives for investing in modern technology and hence enhancing the level of TFP. In particular, a higher level of inequality generates an employment structure which is less agriculture–intensive, besides having a detrimental effect on the innovation process. The latter effect stems out of a demand structure that is not concentrated enough to induce firms to adopt modern technologies in the modern sector (manufacturing and services). The income distribution matters in this, as a more (less) equal distribution generates larger (smaller) markets for each single good. I calibrate the model to the US economy and perform counterfactual experiments with respect to the degree of income inequality. I find that high–inequality economies are characterized by a relatively smaller agriculture sector and substantially worse growth prospects. For instance, doubling the income differentials among rich and poor (from 2 to 4), decreases the equilibrium growth rate of the economy from 2.6 to 1.56%. An increase in inequality implies an increase in the total amount of labor devoted to production, which disproportionately goes into the modern sector (rather than into the agriculture one), as the use of less productive technologies by firms generates the need for more labor (the ratio of agriculture to non–agriculture employment shares drops from 0.122 to 0.116). Instead, when I vary the weight of the different goods in household consumption, a decrease in the size of the agriculture sector is accompanied by improvements in the growth performance. Overall, the model lends a possible explanation of the empirical evidence outlined above.

Acknowledgements

I am and always be greatly indebted to my supervisor Andrés Erosa for his continuous guidance and supervision throughout the years of my PhD. He was always able to strike the difficult balance of being critical towards my work without ever stopping being supportive towards me. I constantly felt I could rely on his help and his advice, especially in the bad moments. Along with him, my greatest gratitude goes to Matthias Kredler for all the time and attention that he devoted to me and for the great comments and suggestions that he gave me during my PhD. I learned a lot in his reading group and in the many endless meetings that I had with him. I sincerely enjoyed being a student of such a professional and enthusiastic professor. Without Andrés and Matthias, this thesis would have not been possible. I feel very lucky to have had the chance to cross my professional and human path with them.

Thanks also to many other faculty members at UC3M, among which I want to mention Ludo Visschers, Hernan Seoane, Pedro Gomes, Jan Stuhler and Emir Yurdagul. Thanks for always being supportive and for helping me in the different phases of the development of my thesis.

I will keep great memories of these years spent in Madrid, especially thanks to all the great friends and colleagues that I had the opportunity to meet. Special thanks to my friend and coauthor Iacopo, with whom I am sure I will continue to work regardless of distance. Thanks to all who shared the office and the many coffee breaks with me, especially Andrés Garcia–Suaza, Federico Masera, Ismael Galvez, Jose Manuel Carbo Martinez, Federico Curci, Michele Rosenberg, Javier Rodriguez and Fabrizio Leone. Thanks to them for all the friendship and fun moments that made this whole experience great, from the football to the beers and the nights out. They probably cannot imagine how much they contributed to my happiness.

I want to deeply thank my family, that always cared for me and never made me feel lonely. This thesis is dedicated to them: to my father Mario, who always represented a model for me; to my mother Paola, who is able to make me feel loved as if I still were a child; and to my brothers Giulio and Beniamino, with whom I want to share this success. Much of what I achieved is only thanks to them.

Thanks to my many friends from Rome, who were always close and supportive despite the physical distance. Among all of them, I cannot avoid to mention Jacopo, Giulia, Enrico and Carlo. I cannot wait to enjoy and celebrate this success with them! Very special and unique thanks go to Irene, whose love and support have been fundamental for this thesis and in many other aspects of my life.

Last, the sweetest thanks go to Carla, who accompanied me in the last part of this long journey with such a deep love that I never thought it could be possible. There are no words that can express my gratitude towards her, and this manuscript is not the proper place to celebrate her. Instead, I hope that a life together will do.

To my dad and my family.

Chapter 1

Parental Links and Employment Prospects: Evidence from the UK

1.1 Introduction

We explore how parental links affect labor market choices and employment prospects of individuals; more specifically, we look at how the job finding and job separation rate are affected by the fact that parents are employed rather than unemployed, and we investigate patterns of occupational mobility across generations. We construct detailed monthly job histories using information from the British Household Panel Survey and exploit information on household structure and friends from the same dataset. In particular, we improve upon the existing literature by linking each individual to his family members, and measuring how the employment prospects of an individual are affected by the labor market status of his relatives or his spouse. Finally, we compare the strength of family ties with that of other relevant ties such as friends.

Our contribution is twofold: first, we document the extent of intergenerational occupational mobility and we argue that using contemporaneous information on parental occupation, rather than retrospective information, is important for measuring such mobility. Second, we establish that the father's employment has an impact on the offspring job finding probability, and we argue that such impact is due to parental networks being an important determinant of employment prospects.

The importance of social networks in determining labor market outcomes has been recognized in the literature in the last decades[1]. Networks are a common way to alleviate

[1] Rees (1966) and Granovetter (1973a) were the first ones to investigate the important role played by social networks in labor markets. Montgomery (1991a) proposed a simple model to capture the features of a labor market with personal connections. More recently, Calvó-Armengol & Jackson (2004) studied the dynamic implications of networks, shedding new light on the

information frictions, largely used by both workers[2] and firms[3].

Our work looks at the workers' side, i.e. individual transitions from unemployment to employment and viceversa. Several papers have tried to quantitatively assess how belonging to a particular network affects labor market variables such as job finding, job separation and wages[4]. One usual shortcoming of the data is that only indirect measures of networks are available. Some researchers rely on estimates of social networks, in order to assess their impact. As a consequence, the estimates produced by these studies are likely to be affected by measurement error, due to the impossibility of exactly identifying the network members. Our work studies social networks at a disaggregated scale and uses direct information on social contacts, thus limiting the extent of measurement error.

The main focus of this work is on parental links. The exogenous nature of parental links –individuals do not choose their parents– makes it easier to quantify their effects and reduces problems of double causality. Fathers and mothers are also commonly recognized to be strong ties in the network literature, and it is therefore interesting to analyze the extent to which parents can influence the labor market choices and outcomes of their offspring.

Moreover, such influence is likely to affect the intergenerational persistence of social and economic status. In this sense, the choice of the data is particularly appealing for our analysis: among developed countries, the UK ranks relatively high in terms of socio-economic persistence across generations[5].

In order to motivate our econometric specification, we first postulate a stylized model of intergenerational transmission of networks in the labor market. In the model, offspring inherit a fraction of the father's network, and then develop their own contacts while employed. As they spend more and more time in employment, the correlation between their employment status and the father's one fades out over time. This motivates our empirical strategy based on difference-in-differences estimation, employing a threshold age to distinguish between treatment and control group. We also report the results of other linear probability models, controlling for individual fixed effects. We show that the effect of parental links is larger when the individual looks for a job in the same occupation of the father. Although one might think that parental links play the most important role in helping the offspring to find his very first job, we document that large and persistent differences in the job finding are related to father's labor market variables for a number of years, rather than only at the beginning

possible effects of policy.

[2]See for instance Holzer (1988) and Pellizzari (2010a).

[3]See for instance Ioannides & Loury (2004) and Topa (2011).

[4]See for instance Topa (2001a), Munshi (2003), Beaman (2012).

[5]The intergenerational earnings elasticity in UK is estimated to be about 0.5, one of the highest among developed countries, again very similar to that of the US, which ranges from 0.5 to 0.6 depending on the estimation method (Corak (2006a)).

of one's career.

To the best of our knowledge, we are the first ones to analyze how parental links affect transitions in and out of unemployment, rather than non-employment as other studies in the literature. We are also the first to document the existence of a strong positive effect of father's employment on these transitions by exploiting direct information on such links. We choose to look at employment and unemployment because the choice of participating to the labor force can be influenced by parental background and employment, which in turn would confound the effect of parental links on nonemployment to employment transitions. By looking at unemployment vs. employment, we are selecting those individuals who are participating to the labor force to begin with.

We document that in the UK occupations tend to be persistent across generations; for instance, sons are from 26 % to 167 % (depending on the sector) more likely to end up working in similar occupations as their fathers, with some exceptions. Similar considerations apply to daughters and mothers.

We find that having an employed (rather than unemployed) father increases the employment rate by about 8 percentage points, with an effect on the job finding rate of at least 5 percentage points, compared to an average in-sample job finding rate of 11 %. Moreover, if an individual searches for a job in the same sector in which his father is currently employed, the effect on the job finding rate is magnified by a further 4 percentage points. Such results are robust to alternative specifications and to several robustness checks. Overall, the evidence is strongly consistent with our model of intergenerational networks. Moreover, by means of a number of empirical tests we are able to rule out several other possible mechanisms that could potentially generate our results. We do not find similar effects for mothers. For the sake of comparison, an additional employed friend increases the job finding rate by 1 - 3 % depending on the estimation method, while the spouse's employment status has a strong association with the individual job finding rate (with a similar magnitude to the father's one).

The rest of the paper is organized as follows. Section 1.2 surveys the literature in greater detail, emphasizing the differences between our work and the others. In Section 1.3 we introduce the data, along with some descriptive statistics of interest. In Section 1.4 we present a stylized model of intergenerational networks, in order to justify the empirical models employed for the analysis (explained in Section 1.5). Results are shown in Section 6 and discussed in Section 7. We performs some robustness checks in Section 8 and conclude in Section 9.

1.2 Related Literature

Our paper relates to the extensive literature on intergenerational occupational and income mobility. In particular, our work suggests two possible sources of income persistence across generations. One is through higher chances of being employed, and the other one is through occupational persistence. As long as wages differ across occupations, then the influence of parental background on occupational choices can be potentially very important in explaining income persistence. The literature on the persistence of income across generations dates back to Becker & Tomes (1986). Solon (1992a) is one of the earliest assessments of the measurement error issues affecting the estimation of intergenerational elasticities, finding high values of persistence for the US. A comprehensive survey of the literature is provided in Corak (2006a), who performs a cross-country study. Jäntti *et al.* (2006) also perform a study of the intergenerational earnings mobility across several countries, while Björklund *et al.* (2012) focuses on Sweden, with a particular emphasis on the top of the distribution. On the link between occupational and income persistence across generations, see also Corak & Piraino (2011a).

We offer direct evidence of the positive impact of family ties' employment on labor market transitions. Many empirical studies try to identify the effect of belonging to a particular network on labor market outcomes. Several papers rely on indirect measures of networks. For instance, Topa (2001a), Bayer *et al.* (2008) and Schmutte (2010) use geographical proximity and group affiliation as proxies for social interactions. Beaman (2012) uses data on political refugees resettled in the US and proxies for networks using nationality. Overall, these studies find evidence of positive effects of social interactions on labor market outcomes. Similarly, Khan & Lehrer (2013) use a random assignment to a unique intervention to identify the impact of changes in the size of a social network. Access to the program successfully led to gains in the number of weak ties but these changes did not translate into improved employment outcomes. Herault & Kalb (2009) look instead at parental links; using retrospective parental information from Australian data, they find significant persistence in employment across generations.

Our paper is more closely related to that strand of this literature that exploits direct identification of network members.

O'Regan & Quigley (1993) study the correlation of employment status of urban youth with the employment status of their family members (parents and siblings) in the US, finding strong and positive correlations. Further, they observe that the industry affiliation of the network members is a good predictor of the industry affiliation of the individual. Magruder

(2010) examines to which extent parents help children in finding jobs in South Africa. He finds that fathers help sons (but not daughters), while mothers are not helpful in finding jobs. Differently from these works, our analysis is dynamic and focuses on transitions from unemployment to employment and viceversa, rather than on employment status versus nonemployment. Also, our data allows us to employ different estimation techniques and to compare parental effects to similar effects by other strong ties. Kramarz & Skans (2014a) investigate parental networks at the firm-level. They analyze Swedish graduates, finding that it is quite frequent that their first job is in the same plant where their parents work. With respect to their paper, rather than focusing only on the entry in the labor market, we follow individuals over their life-cycle, investigating whether the advantages derived from their network persist over time.
Finally, Pistaferri (1999) uses Italian data and finds that informal networks use is associated with higher job finding rates and lower wages. Similarly, Bentolila *et al.* (2010a) find that individuals who use social contacts to find their job are characterized by higher job finding rate (lower unemployment duration) and slightly lower wages. They suggest that the trade-off between job finding rate and wage could still make individuals choose to enter the same sector as their network members. Indeed, we document patterns of intergenerational persistence in occupations; along with our regression results, this is consistent with a model of occupational choice in the spirit of Bentolila *et al.* (2010a).
Closely related to our work is the study of Cappellari & Tatsiramos (2011), who also use data from the BHPS and a similar methodology. Nonetheless, some relevant traits differentiate the two works: first, we focus on parental links, instead of friendship ones; second, we identify monthly transitions (rather than yearly); third, we look at transitions within the labor force while they consider transitions from non-employment to employment; fourth, we document how searching for a job in the same occupational sector magnifies the effects we find.

Several studies in the literature have tackled the issue of understanding the effects of social networks by means of a theoretical model. One of the first papers to include personal contacts in a job search framework was Mortensen & Vishwanath (1994). In their model the information about vacancies comes from two different sources: direct application to employers or indirect contact through friends. As a consequence, better connected individuals have more chances to find a job. Similarly, Montgomery (1991a) finds that well connected workers perform better in the labor market, both in terms of wages and of higher job finding rates. Calvó-Armengol & Jackson (2004) also develop a model where workers can obtain information through an explicitly modeled network of social contacts. In their model, belonging to a network with less employed members implies worse employment prospects, and this effect is persistent over time. Other models of networks and job search are in Fontaine (2008) and Calvó-Armengol & Zenou (2005), with a particular focus on networks' dynamics. More recently, Galenianos (2014a) embeds networks explicitly into a search and matching model and finds that referral mechanisms have important macroeconomic implications.

A distinctive feature of all these works is that networks exhibit a positive effect on labor market outcomes of individuals. These studies constitute the theoretical ground on which we base the interpretation of our results.

1.3 The Data

We use data from the British Household Panel Survey, a representative sample from the UK following individuals since 1991. The BHPS is a yearly survey taken by about 10,000 individuals per year and the last available wave for this study is 2008. The follow-up rate is very high and the great majority (more than 90%) of individuals are interviewed also in the subsequent year. Besides these, every year a certain number of new individuals enter the sample. A total of 32,377 individuals are interviewed in the BHPS in the period 1991-2008. Even though the survey is yearly, individuals report their job history in the last year, listing all the employment (unemployment) spells along with several characteristics of each job. This allows us to identify monthly transitions and build long time series for each individual, up to 216 months. Details on how we construct job histories for individuals are included in Appendix A.

We retrieve the employment status of individuals exploiting the job histories, distinguishing between employees and self employed. The employment status of individuals is assigned at the monthly frequency. Differently from other studies, we do not consider individuals who are out of the labor force in our transitions. We define the job finding rate as the probability of transiting from unemployment (rather than non-employment, as for instance in Cappellari & Tatsiramos (2011)) to employment. The job separation rate is defined accordingly. We restrict our sample to individuals aged between 16 and 65[6] and, as it is standard in the literature, we drop armed forces and registered disabled. Eventually we are left with 27,278 individuals, for a total of 2,232,528 monthly observations.[7]

[6]That is, our intergenerational sample will include couples of parents and offspring if and only if both are in this age range.

[7]We also check whether our final sample is representative of the UK economy between 1991 and 2008. We compute the in-sample unemployment rate and compare it with the harmonized unemployment rate according to OECD statistics (figure 10

Along with a detailed job history, for each individual a large amount of information is typically available, including sex, age, education, occupation, race, marital status, region of residence and much more. More interestingly, the identification number of parents and spouse is available, allowing us to connect individuals to their family members and follow them together over time[8]. In addition to this, the data include information on the employment status of the three closest friends and the occupation of the closest friend. This information is collected only every second wave, starting in 1992. At the core of the analysis, we consider the relationship between the employment status (and the occupation) of the parents and the employment prospects of respondents. We also compare parental effects to similar effects by spouse and friends. Since friends' job histories are not reported, in order to keep the monthly frequency we extend their employment status and occupation in the following 12 months after each observation. Furthermore, we use a simple procedure to attribute the occupational sector to unemployed and to extend non-varying or spell-dependent variables, as described in Appendix A. Especially for the occupation, the data contain many missing values, both for respondents and connected individuals: we assume that these values are missing at random and simply exclude the incomplete observations from the estimation, when it is not possible to replace them according to the procedure described in Appendix A. The final size of the estimating sample varies, depending on the dependent variable we use in each regression[9].

Table 7 (in Appendix 3.7) displays some descriptive statistics of interest for our analysis. As we can see, the period 1991-2008 is characterized by a relatively low level of unemployment in the UK. More than 93% of the population in the labor market has a job, 12% of which is self employed. The average monthly job finding rate, that is the probability of transition from unemployment to employment, is slightly above 7%. Conversely, the average job separation rate is relatively small (0.4%). This implies that in the period considered the UK economy was characterized by a high level of security for those who had a job. On the other hand, it was somewhat hard to find an occupation for those who were unemployed: on average, the expected waiting time in unemployment was about one year. In other words, the reason behind the low unemployment rate is the tightness of the monthly outflow from employment rather than a large inflow from unemployment. Compared to other OECD countries, the UK economy has an average performance in terms of search variables[10]. A

in the Appendix). The average unemployment rate of our sample replicates quite well the pattern of the OECD series.

[8]Unfortunately, it is possible to do so only for about 19% of the whole sample for fathers and 25% for mothers (those who report the parental PID numbers).

[9]By construction, the job finding rate (job separation) is defined only over unemployment (employment) spells.

[10]For a cross-country comparison of estimates of the standard search variables see Hobijn and Sahin (2007). As shown by other studies, the European economies perform much worse than the US to this extent. For instance, the job finding rate is estimated to be about 30%-40% in the US (Shimer (2012)).

comparison among genders shows that females in the labor force tend to have slightly better outcomes than males. About 53% of our sample is female and the average individual is aged 39. We define four educational groups and nine occupational sectors, following the SOC aggregation by major group, as established by the Employment Department Group and the Office of Population Censuses and Surveys. We identify an occupational sector $O_{i,t}$ for each individual (parents included), for both unemployed and employed individuals. When employed, the occupational sector is defined in a straightforward manner. When unemployed, the occupational sector is interpreted as the sector in which the individual seeks for a job, and is assumed to be the one in which the individual eventually finds a job. For instance, if an individual i starts being unemployed at time t, is unemployed for 10 months and then finds a job in sector 3, we assume that the individual was indeed searching in sector 3 for those 10 months: $O_{i,t} = O_{i,t+1} = ... = O_{i,t+10} = 3$. If we have no information on the occupation of arrival, for instance because the individual exits the sample or goes out of the labor force, we use the occupation prior to the unemployment spell when available. The rationale behind our choices and further details are explained in Appendix A[11]. The distribution of workers across occupational sectors is shown in Table 1.1, along with several labor market statistics of the sectors.

Table 1.1. Distribution of workers across sectors and sectoral labor market statistics. Source: BHPS (1991-2008)

Occupational Sector	Abs. Freq.	Rel. Freq.	Unempl. Rate	JF Rate	JS Rate
Managers & Administrators	221396	14.88	2.08	10.15	0.25
Professional	147698	9.92	1.82	11.96	0.20
Associate Professional & Technical	174160	11.70	2.59	11.18	0.22
Clerical & Secretarial	235157	15.80	4.35	12.16	0.43
Craft & Related	178628	12.00	6.22	8.10	0.53
Personal & Protective Service	170551	11.46	6.72	8.03	0.52
Sales	108502	7.29	6.39	10.59	0.62
Plant & Machine	131936	8.86	7.82	8.95	0.67
Agriculture & Elementary	120345	8.09	9.66	7.55	0.73
Total	1488373	100.000	4.94	9.38	0.43

We see that labor market outcomes are not independent from sectors. While it is known that high-skilled jobs are better paid, it seems like there are also relatively large differentials in terms of unemployment rate (and search variables). One possible explanation is a relative scarcity of high-skilled workers in the UK in those years, compared to the high profitability of those sectors (managerial and professional). In the first three sectors the unemployment rate ranges between 1.8% and 2.1%, with a job finding rate of 10-12% and a job separation rate of about 0.2%. On the other hand, we also notice that restricting

[11] Our results are robust to alternative assumptions: we tried using only the future occupation, the past occupation or a combination of the two.

the sample to the observations for which the occupation is available induces some degree of sample selection. The average job finding rate (unemployment rate) is indeed higher (lower) than in the whole sample. This happens because originally all the individuals assigned to a sector are employed, and our sector imputation only considers the next and the last labor spell. Therefore, due to the large number of missing values for occupation, we lose many observations of unemployed (typically, the long-term unemployed) when imputing the sector. Unfortunately, without making any stronger assumptions than the ones we already make, it is not possible to get rid of this issue. However, notice that the sample selection problem only affects the unemployment rate and the job finding rate, as shown in Table 1.1.

1.3.1 Patterns of Occupational Mobility across Generations

While many studies on occupational mobility across generations rely on single observations for the occupation of parents, the BHPS allows us to follow parents over time. In this way, besides the answer to "What was your parents' occupation when you were 14?", our data provides a better source of information on parents' side.
First of all, we compare the distributions of parents and offspring across sectors. Table 1.2 shows the distribution of sons and daughters, parents when offspring (respondents) were 14 and parents who are followed over time. We immediately notice that a large degree of sex segregation characterizes the distribution across sectors. Managerial and craft occupations are typically covered by men, while secretarial and sales jobs are more intensively taken by women. This phenomenon seems to be persistent over generations, given that no relevant differences can be detected when comparing the distribution of offspring and parents to this extent. Another interesting feature is the large structural change that characterized the UK economy in the last decades. Sectors such as craft or machine occupation shrunk significantly in relative terms, while managerial, professional and especially technical occupations employ nowadays a larger share of the working force than before. For this reason, the distribution of offspring is more directly comparable with the distribution of parents who are followed over time, as in this way we are comparing occupational choices within the same economy.

In what follows, we argue that there exist important differences in occupational mobility computed using retrospective information and using contemporaneous information, and that these differences are crucial for understanding occupational mobility across generations. In order to investigate the degree of occupational mobility across generations we build Markov matrices, computing the transition probabilities from a sector to another. As parental oc-

Table 1.2. Distribution of sons and parents across sectors, relative frequencies. Source: BHPS (1991-2008)

	Offspring 1991-2008		Parents when offspring 14		Parents 1991-2008	
Occupational Sector	**Sons**	**Daughters**	**Fathers**	**Mothers**	**Fathers**	**Mothers**
Managers & Administrators	18.92	11.96	16.81	7.36	22.48	9.90
Professional	10.23	10.60	8.05	6.04	8.69	9.19
Associate Professional & Technical	10.83	13.35	4.05	7.61	7.11	9.19
Clerical & Secretarial	7.91	24.39	5.00	19.16	6.41	25.61
Craft & Related	21.12	2.12	27.44	5.40	22.43	2.20
Personal & Protective Service	5.90	16.55	5.11	14.90	4.70	18.06
Sales	4.60	9.81	3.71	11.66	4.36	10.87
Plant & Machine	13.41	3.29	18.26	7.84	18.35	3.82
Agriculture & Elementary	7.07	7.93	11.58	20.03	5.46	11.16
Total	100.00	100.00	100.00	100.00	100.00	100.00

cupation, we use both the current one and the one as reported when offspring were 14. If individuals rarely switch occupation over the life cycle, the two sources of information on parental occupation will be highly correlated. Consistently with the degree of sex segregation that we found in the data, we report the tables for couples of the same gender: fathers with sons, and mothers with daughters. For males, even though with some heterogeneity, we note that there is a general level of persistence in the same sector as their father's one as reported when respondents were 14. Table 1.3 reveals that the persistence is particularly high at the top (managerial and professional occupations) and at the bottom (plant and machine occupations) of the distribution, with another peak for craft occupations. Instead, when considering the contemporaneous occupation, persistence drops significantly at the top while it strongly increases in the mid-sectors.

When considering women (in Table 1.4), similar considerations can be made: for instance, the persistence with mother's sector as reported when daughters were 14 is strikingly high for managerial and professional occupations. Again, when we look at the contemporaneous occupation, the persistence at the top almost disappears while it becomes more substantial in the middle and at the bottom of the distribution. Overall, women are very attached to clerical and secretarial occupations: the probability of falling into that category is very high regardless of parental background.
The large differentials in the patterns of persistency obtained by using retrospective instead of current information on parental occupations implies the existence of a substantial degree of occupational mobility of parents over their life cycle. Tables 8 and 9 (in the Appendix) show that fathers and mothers have a sizeable probability of moving between occupations during their worklife. Studies that focus only on retrospective information on parental oc-

Table 1.3. Markov matrix of occupational mobility: fathers-sons, relative frequencies. Source: BHPS (1991-2008)

	Son's sector								
Father's sector when son is 14	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**31.99**	13.76	12.42	6.44	12.56	5.10	4.38	8.30	5.06
2	23.72	**26.11**	21.35	7.55	6.51	4.04	3.38	4.65	2.69
3	25.86	15.75	**17.53**	7.84	12.67	5.16	3.35	8.72	3.13
4	16.98	16.94	13.80	**12.07**	16.71	4.97	3.26	9.69	5.57
5	16.65	9.55	9.32	7.43	**27.86**	5.31	3.76	13.73	6.40
6	18.26	11.61	11.81	10.02	17.87	**8.68**	5.33	11.73	4.68
7	25.09	9.73	13.27	8.88	15.46	2.52	**8.42**	11.55	5.07
8	15.06	7.03	8.38	6.50	24.20	6.50	3.66	**22.13**	6.55
9	14.52	5.47	6.44	7.43	25.18	4.49	4.63	19.37	**12.47**
Father's sector contemporaneous	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**13.46**	7.51	13.11	11.80	22.34	6.94	10.26	5.49	9.09
2	10.77	**13.32**	19.95	16.82	13.02	5.97	10.71	4.46	4.98
3	9.22	7.92	**19.74**	18.96	15.47	5.18	8.36	10.00	5.16
4	13.65	7.85	16.44	**16.03**	17.37	3.82	8.18	10.20	6.46
5	7.99	1.64	8.78	10.95	**40.49**	5.39	7.32	10.28	7.16
6	12.20	1.76	11.69	18.40	17.66	**16.93**	6.87	6.64	7.86
7	7.76	6.47	14.77	13.22	21.95	8.95	**9.95**	11.89	5.03
8	8.95	2.26	6.70	8.50	30.91	7.89	5.51	**20.89**	8.39
9	6.16	4.61	13.16	12.31	23.45	5.35	5.65	8.18	**21.13**

Table 1.4. Markov matrix of occupational mobility: mothers-daughters, relative frequencies. Source: BHPS (1991-2008)

	Daughter's sector								
Mother's sector when daughter is 14	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**18.77**	12.38	15.46	20.77	1.94	15.32	9.03	1.06	5.26
2	13.96	**30.97**	17.75	19.36	0.58	9.26	4.83	0.56	2.73
3	14.72	12.54	**21.03**	21.81	1.28	15.51	6.20	1.95	4.96
4	13.78	16.87	16.28	**29.64**	1.74	11.70	5.51	1.09	3.40
5	12.44	8.30	10.85	22.72	**2.92**	16.39	11.65	4.39	10.33
6	10.86	8.15	13.39	23.85	2.03	**20.11**	9.43	2.57	9.60
7	12.79	8.55	11.93	29.41	1.71	14.61	**11.92**	3.15	5.92
8	10.32	5.02	8.97	26.61	2.76	17.93	10.25	**6.98**	11.15
9	8.89	6.29	13.21	21.58	1.98	20.26	11.50	4.18	**12.12**
Mother's sector contemporaneous	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**16.74**	13.52	9.61	21.04	0.58	19.90	10.83	1.27	6.51
2	13.50	**15.91**	17.27	25.06	1.93	11.80	10.59	0.53	3.41
3	10.01	9.99	**14.89**	25.73	1.30	23.05	9.59	1.35	4.08
4	10.75	7.51	10.45	**37.10**	0.87	18.49	11.01	0.44	3.37
5	6.00	9.25	0.89	23.13	**9.65**	19.29	24.80	3.74	3.25
6	8.07	7.17	10.85	25.41	1.19	**24.59**	16.28	1.15	5.29
7	5.60	3.25	6.02	31.47	2.74	23.57	**18.31**	5.30	3.74
8	6.54	0.94	4.79	23.47	5.87	24.61	13.01	**10.92**	9.84
9	14.12	5.04	9.23	30.27	1.03	19.23	13.98	2.78	**4.31**

cupations cannot account for this important feature of the data.
In order to ease the interpretation of the statistics just shown, we construct likelihood ratios dividing the probabilities shown in the diagonal of the matrix by the unconditional probability that a son (or daughter) belongs to each particular sector. This produces a synthetic measure of the "effect" of parental occupational sector on individual choices. Table ?? shows that, when compared to the actual job distributions, the attachment to parental sector is indeed very large. On average, sons (daughters) are 76 % (191 %) more likely to be in the father's (mother's) occupational sector than expected if the assignment of sector was random.

Table 1.5. Likelihood ratios: each cell represents the probability that a son (daughter) belongs to a given occupational sector conditional on father (mother) being in the same sector, divided by the unconditional probability of belonging to that sector. Results are shown separately by gender (sons with fathers, and daughters with mothers). Source: BHPS (1991-2008)

Occupational sector contemporaneous	**Likelihood ratio Males**	**Likelihood ratio Females**
Managers & Administrators	1.29	1.93
Professional	2.59	2.36
Associate Professional & Technical	1.63	1.72
Clerical & Secretarial	1.26	1.55
Craft & Related	1.55	7.26
Personal & Protective Service	1.58	1.44
Sales	1.34	1.73
Plant & Machine	1.94	7.07
Agriculture & Elementary	2.67	1.17

In the next subsection, in order to understand and interpret the patterns of occupational persistence, we study whether parental labor market variables (such as their employment status and their sectoral belonging) affects individuals' labor market outcomes.

1.3.2 Employment Prospects across Generations

Before entering the regression-based analysis, we look at the relationship between labor market performances across generations. In particular, we compute the average unemployment rate and search variables of individuals conditional on the employment status of parents. We also investigate whether these intergenerational correlations vary when individuals are in the same occupational sector as their parents.

Table 1.6 reveals the existence of strong correlations across generations. Having employed (rather than unemployed) parents is associated with better labor market outcomes. For instance, the average unemployment rate –which is 21% for those whose father is unemployed– drops to 8% for those whose father is employed, decreasing further up to less than 5% when the father is in the same sector as the offspring. Similar percentages

Table 1.6. Employment prospects across generations: unemployment rate, JF and JS rate conditional on parental employment status/occupation. Source: BHPS (1991-2008).

		Father			Mother		
Variable	**Subsample**	**Unemployed**	**Employed**	**Same Sector**	**Unemployed**	**Employed**	**Same Sector**
Unemployment Rate	All Sample	20.67	7.84	4.74	17.86	7.86	7.38
	Males	24.14	9.11	5.02	20.83	9.18	8.02
	Females	14.35	6.23	4.01	15.17	6.28	6.87
Job Finding Rate	All Sample	4.85	11.02	15.23	7.45	11.05	12.89
	Males	4.88	10.58	14.85	7.65	10.64	14.17
	Females	4.86	11.82	16.13	7.20	11.79	11.68
Job Separation Rate	All Sample	1.16	0.75	0.58	1.23	0.74	0.79
	Males	1.34	0.85	0.58	1.42	0.84	0.94
	Females	0.87	0.62	0.57	1.07	0.63	0.66

characterizes the mother's employment status, with the difference that there does not seem to exist any additional effect linked to sector belonging. The job finding rate more than doubles on average (it increases from 4.9 to 11%) when the father is employed, while the effect of the mother's employment status is less pronounced but still large (from 7.4 to 11%). Again, when the father is employed in the same sector, individuals experience an even higher job finding rate on average (about 15%). Interestingly, the job finding rate of males appears to be affected also by having the mother in the same sector. Finally, the job separation rate is also correlated with parents' employment status in the same direction. It is roughly 1.1% for those with unemployed father and it drops to 0.75% for those whose father is employed. Mother's employment status has approximately the same effect on this conditional average. An extra reduction in the job separation rate is found when the sector of the offspring coincides with the one of the father, while no relevant differences with respect to the sector of the mother.

Overall, significantly better labor market performances are found to be associated with the employment status of the parents. Such advantages are larger when individuals are in the same occupational sector as their father. The additional premium is about 40-50% the size of the effect of having an employed father[12].

We investigate whether the differences between these groups change over the life cycle. We find that especially for the very young the difference is very large. Figure 1.1 shows that having the father employed is associated with up to 20 to 30 percentage points more in the average employment rate. This difference steadily declines over the life cycle and eventually disappears. The higher employment rate[13] can be generated by higher job finding rates,

[12]Remarkably, we do not find that these patterns are substantially different by gender.

[13]It is defined as $1 - unemployment\,rate$.

lower job separation rates or a combination of the two. Figure 1.2 and 1.3 reveal that the job finding rate is driving the bulk of the difference, yielding large and persistent variations across groups. Conversely, the job separation is substantially lower for offspring of employed fathers especially at early ages, whereas the gap greatly reduces later on in the life cycle. Nevertheless, small differences in absolute value are actually large in relative terms and have a strong impact on individual worklife.

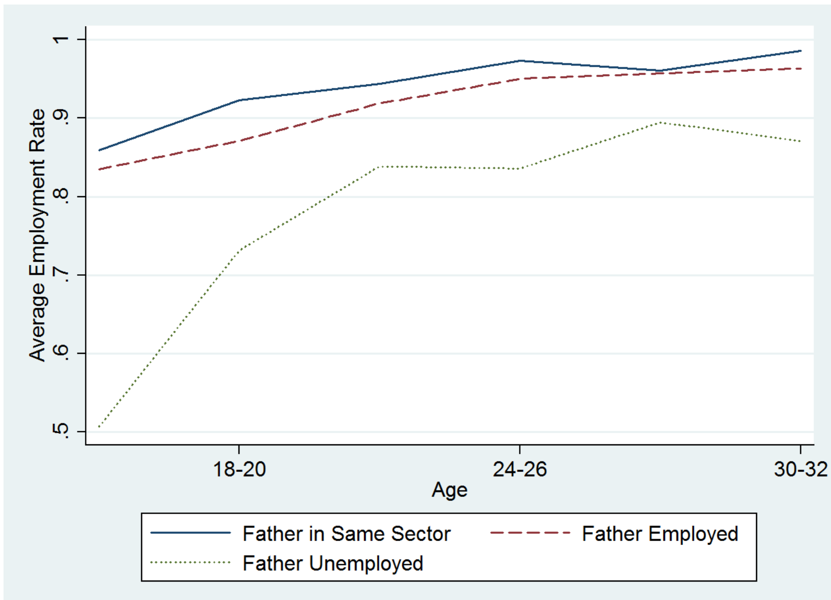

Figure 1.1. Employment Rate (Employed 1, Unemployed 0) as a function of age: cross sectional averages. Source: BHPS.

The correlations found so far are interesting per se, even though they do not necessarily represent any direct effects of parents on offspring' labor market outcomes. Several other correlations, for instance educational attainment, human capital accumulation or genetical transmission, might well explain these differences in the conditional averages. Moreover, it could also be the case that respondents' outcomes affects parental ones, instead of the other way around. In any case, the differences in the other observables across these groups (Table 10 in Appendix 3.7) are not large[14]. In Section 1.5 we outline our empirical strategy to address these and other related issues, in order to try to establish a causal relationship and estimate the effect of parental links on offspring' employment prospects.

Before that, we now proceed to postulate a simple of model of intergenerational networks, in order to motivate our empirical strategy and illustrate the source of variation we want to exploit for the identification of a causal relationship.

[14]Not surprisingly, those who belong to the same sector as their father tend to be more often males. Also, they are slighlty older, more educated, more often married and white.

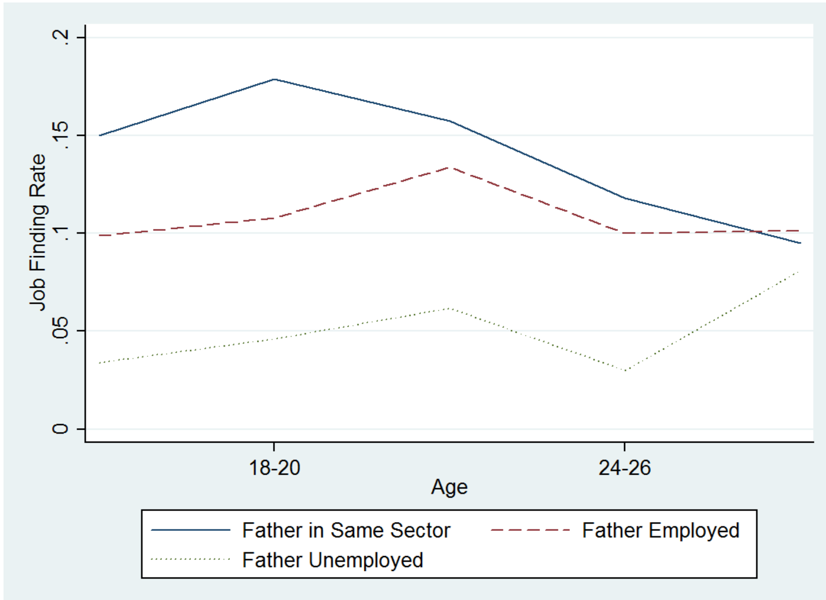

Figure 1.2. Job Finding Rate as a function of age: cross sectional averages. Source: BHPS. Ages 30-32 are cut because of limited availability of observations.

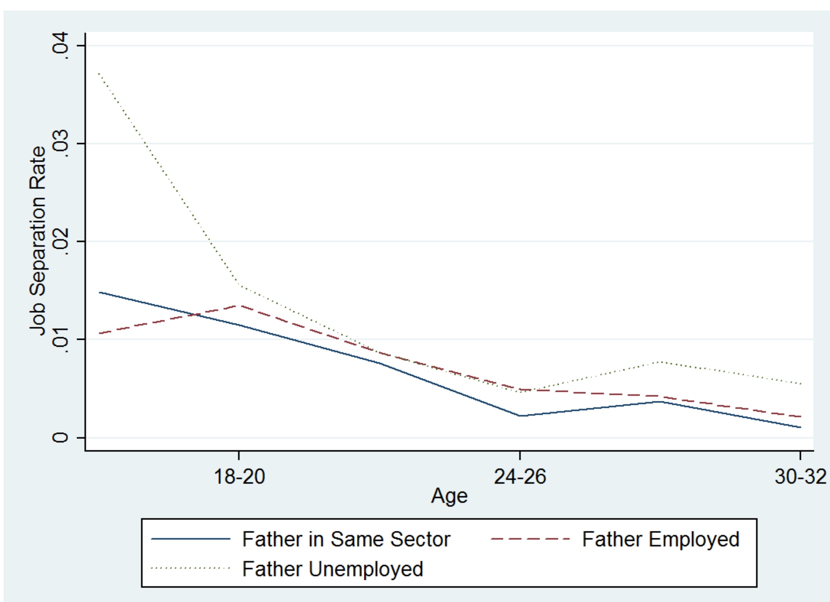

Figure 1.3. Job Separation Rate as a function of age: cross sectional averages. Source: BHPS.

1.4 A Simple Model of Intergenerational Networks

This model is a simple adaptation of Calvó-Armengol & Jackson (2004). Individuals look for jobs when they are unemployed, and in order to do so they exploit their network of social contacts. Employed parents help their unemployed offspring in that they let them use their own social network.

Suppose the economy is populated by identical workers, indexed by worker i, family j and age t. Every period, all workers of age T have an offspring of age 0. We assume that individuals stop being connected with their parents when they have children, so that at each point in time only two generations are connected[15]. In the first period of their lives ($t = 0$), agents draw an initial network size $n^j_{i,0} = \epsilon^j_{i,0}$ from a normal distribution. From that moment onwards, the total network of an offspring ($t < T$) at time t is denoted by $\hat{n}^j_{i,t}$ and it is given by the following expression:

$$\hat{n}^j_{i+1,t} = \beta n^j_{i,t+T} S^j_{i,t+T} + n^j_{i+1,t} \qquad \forall t < T \tag{1.1}$$

where $i+1$ represent the offspring of father i within family j, $n^j_{i,t}$ denotes the natural logarithm of work connections held by worker i in family j at time t and $S^j_{i,t+T}$ denotes the employment status of the father i at age $t+T$.

Fathers' total networks necessarily have to coincide with their personal networks:

$$\hat{n}^j_{i,t} = n^j_{i,t} \qquad \forall t \geq T \tag{1.2}$$

Workers can be in either of two states $S \in \{E, U\}$, employed or unemployed. When employed, they lose their job with constant probability γ. Work connections positively affect the probability of finding a job, as such connections allow workers to reduce informational frictions. Hence we have that, when unemployed, the job finding probability f is:

$$f^j_{i,t} = 1 - e^{-\hat{N}^j_{i,t}} \tag{1.3}$$

where $\hat{N}_{i,t} = e^{\hat{n}_{i,t}}$. We assume that the timing is as follows: first, shocks to the employment status (f and γ) take place; second, personal networks $n^j_{i,t}$ evolve stochastically according to the following law of motion:

$$n^j_{i,t+1} = \begin{cases} \alpha + (1-\delta^E) n^j_{i,t} + \epsilon^j_{i,t} & \text{if } S^j_{i,t} = E \\ (1-\delta^U) n^j_{i,t} + \epsilon^j_{i,t} & \text{if } S^j_{i,t} = U \end{cases} \tag{1.4}$$

[15]This assumption is made for simplicity and does not alter our results.

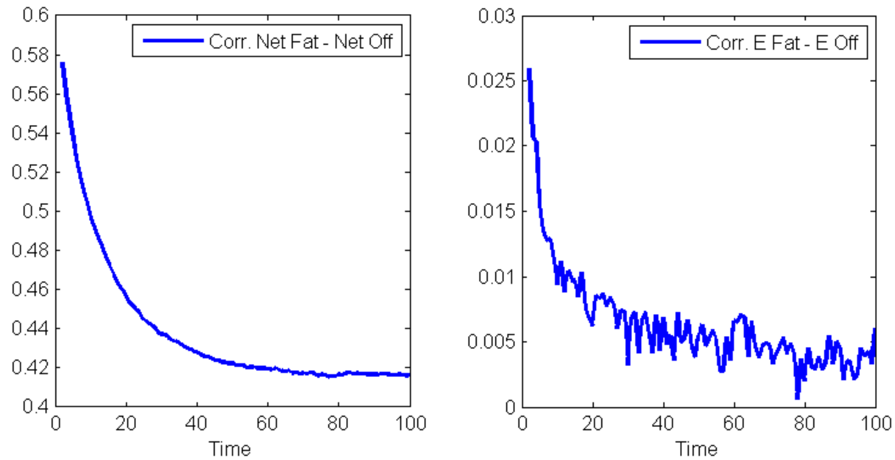

Figure 1.4. Simulated correlation between fathers and offspring **network** (left) and **employment status** (right). $\alpha = 0.05, \beta = 0.5, \delta^E = 0.03, \delta^U = 0.03, \gamma = 0.05$.

where $\epsilon_{i,t}^{j} \sim \mathbb{N}(0, \sigma^{\epsilon})$. These equations encompass the idea that a worker gains useful connections while working, and may randomly lose/gain more connections every period. While not working, however, such connections depreciate every period because workers progressively lose contact with their former colleagues. In principle the rates of depreciation $\{\delta^E, \delta^U\}$ do not need to be equal, but the difference between them is not important for our results.

It is clear that the correlation between labor market status of fathers and offspring is highest for $t = 0$; at the initial period, connections of offspring are mainly defined by those of their fathers because the former did not have the opportunity yet to form many useful work connections. As time goes by, the careers of fathers and offspring evolve independently and those that were common contacts at the beginning might be still useful contacts for one, but lost touch with the other. As a consequence, the correlation between labor market status fades out along with the correlation between parental and offspring's networks.
Showing formally that the covariance between the employment status of fathers and offspring dies out over time is not straightforward, because the correlation at one point depends on the whole history of employment/unemployment of both the father and the offspring. However, we provide simulation results to show that indeed such correlation fades out as workers get older. These results are shown in Figure 1.4, in which we assign values to the parameters of the model and report the results of our simulations.

Another way to see that differences induced by initial networks vanish over time is to look at the probability of being employed over the life cycle, by different initial conditions. Figure 1.5 shows how individuals with high, rather than low, initial networks have a higher

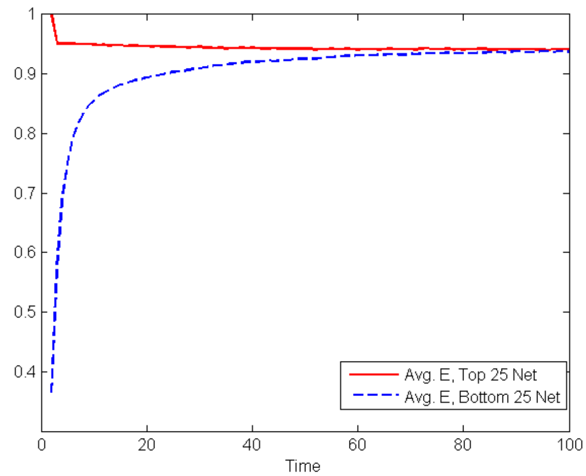

Figure 1.5. Simulated paths of average employment status for individuals with **high** (red line) and **low** (blue line) initial networks. $\alpha = 0.05, \beta = 0.5, \delta^E = 0.03, \delta^U = 0.03, \gamma = 0.05$.

probability of being employed at the beginning of their careers; as time goes by, such difference goes to zero, as we observe in the data.

Shocks to the employment status of the father will have an impact on the employment prospects of offspring mostly at the beginning of their career. This motivates our strategy of looking at the difference in correlation of employment status between ages 20-30 and later ages. As careers evolve independently, the correlation fades out and offspring after age 30 constitute a proper control group for identifying the effect of networks early on.

1.5 Empirical Strategy

We are interested in understanding the partial correlation between individual employment prospects[16] and the employment status of their parents. First of all, we define an employment status variable $E_{i,t}$ using information on job histories. $E_{i,t}$ is equal to 1 if individual i is employed at time t, and 0 in case of unemployment. In all periods of different labor market status (retired, in further education etc.), $E_{i,t}$ is not defined.

Then we define the transition variables $J^f_{i,t}$ and $J^s_{i,t}$, respectively the job finding and job separation events for an individual. $J^f_{i,t}$ is a dummy variable that takes value 1 if individual i moves from unemployment to employment at time t (that is, $E_{i,t-1} = 0, E_{i,t} = 1$), and 0 if the individual remains unemployed ($E_{i,t-1} = E_{i,t} = 0$). In all periods of employment or labor market status different from unemployment, $J^f_{i,t}$ is not defined. Conversely, $J^s_{i,t}$ takes

[16] As of now, the focus of our analysis is exclusively on individual employment status and transitions from unemployment to employment (and viceversa). In future work, we are planning to include the wage in our analysis.

value 1 in case of transitions from employment to unemployment and zero otherwise.

Next, we link individuals and parents using personal identification numbers of relatives provided in the BHPS. For all individuals i for which such information is available, we associate a father, a mother, a spouse and three friends. Call $E_{i,t}^{\textbf{father}}$ the employment status of the father of individual i at time t and similarly for the mother, the spouse and all friends.

In principle we could just use the raw employment status data in our regressions. However, since we have monthly job histories, we are not capable of determining precisely whether jobs ending at time t are covering the full month representing time t or only a small portion of it. The problem is relevant because a correct identification of the timing of spells is crucial to correctly estimate the partial effect of interest: suppose for instance that a father is employed until December 20th when he becomes unemployed, while his offspring obtains a job on December 10th. Since job histories are written in monthly format, it is possible that the father will result unemployed in December, while his offspring will result employed from December onwards. However, it is not clear whether we should have considered the father employed rather than unemployed, since the labor market spell of his offspring began during his employment spell. In order to exclude these controversial cases, we consider only labor market statuses that are unambiguously assigned in a given month, that is we exclude those cases in which the labor market spell changes between two months. Basically, instead of using $E_{i,t}^{\textbf{Father}}$ as defined above, we use

$$E_{i,t}^{\textbf{Father, ongoing}} = \begin{cases} E_{i,t}^{\textbf{Father}} & \text{if } E_{i,t+1}^{\textbf{Father}} = E_{i,t}^{\textbf{Father}} \\ \textit{missing} & \text{if } E_{i,t+1}^{\textbf{Father}} \neq E_{i,t}^{\textbf{Father}} \end{cases}$$

We construct similar variables for mothers and, for comparison purposes, spouses.

1.5.1 Difference-in-Differences Estimation

In order to identify the effect of parental networks on employment prospects, we divide our sample in two groups, one of which is assumed not to be affected by parental networks. Consistently with the stylized model presented in Section 1.4, the control group is made up by all those workers who are not very young anymore. In particular, we employ an age threshold of 27 for discriminating between control and treatment group[17]. The rationale behind this definition of the control group is that individuals accumulate social contacts while working so that their pool of contacts become more and more different from those of their family connections over time. For this reason, an alternative definition of the control

[17]Results are robust to changes in the threshold age. Using any age between 25 and 29 yields a coefficient that yields between 6 and 8 p.p., that is significantly different from zero.

group is based on the experience of individuals[18]. For both definitions of control group, we run linear[19] regression models of the form

$$Y_{i,t} = \beta_0 + \beta_1 E^{\textbf{Father, ongoing}}_{i,t-1} + \beta_2 T_{i,t} + \beta_3 T_{i,t} E^{\textbf{Father, ongoing}}_{i,t-1} + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{1.5}$$

where $T_{i,t}$ takes the value 1 if the individual belongs to the treatment group (as explained before). The employment status of the father $E^{\textbf{Father, ongoing}}_{i,t-1}$ has a one period lag, in order to avoid problems of double causality (i.e. when the offspring is employed, the father becomes employed thanks to the offspring). $\mathbf{X}_{i,t}$ is a vector of control variables and the dependent variable $Y_{i,t}$ will be, alternatively, the employment status, the job finding rate $J^f_{i,t}$ and the job separation rate $J^s_{i,t}$. Controls will include a third degree age polynomial, dummies for gender, education, occupational sector (observed for employed, imputed for unemployed), marital status, ethnic group, smoking behaviour, region of residence and quarterly dummies. We are interested in the estimation of β_3, which will give us the effect of parental networks on labor market outcomes. The identifying assumption is that all other factors affecting the outcome variable other than parental networks affect the offspring of employed and unemployed in the two groups in the same way. That is, we only need that the relative difference in the way these factors affect individuals remains unchanged across the treatment and the control group. Under this assumption, our estimator $\hat{\beta}_3$ will identify the effect we are looking for:

$$\hat{\beta}_3 = (\bar{Y}_{T,E^F=1} - \bar{Y}_{T,E^F=0}) - (\bar{Y}_{C,E^F=1} - \bar{Y}_{C,E^F=0})\,. \tag{1.6}$$

1.5.2 Other Linear Probability Models

In order to check that our results hold when changing the model specification, we also employ three other types of regressions: Pooled Ordinary Least Squares, Random Effects GLS and Fixed Effects. In this case we do not use any control group and our identification strategy with FE estimation estimation crucially depends on the time-invariance of the other factors affecting the outcome variables. The estimating model is a reduced version of the previous one and reads as follows

$$Y_{i,t} = \beta_0 + \beta_1 E^{\textbf{Father, ongoing}}_{i,t-1} + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{1.7}$$

[18] In a robustness check, we define the control group as those workers who have at least a given number of years of potential experience (defined as years elapsed after the completion of education) in the labor market.

[19] In principle, linear models are not ideal for analyses that involve probability because they might predict negative or bigger than one probabilities. We choose linear models over probit/logit formulations because of the easier interpretation of marginal effects. When we run similar logistic regressions, we obtain substantially the same results. Results are now available upon request and will be included in the Appendix of a future version of the paper.

We are interested in the estimation of the coefficient β_1. While the POLS is the standard empirical baseline, we are more interested in empirical models that exploit the time structure of the data. In particular, the time-invariant individual heterogeneity captured by the Fixed Effects estimator might affect our results significantly if fixed individual characteristics not captured by controls $\mathbf{X}_{i,t}$ are correlated with labor market outcomes of parents[20]. We run such regressions for both parents and, for comparison purposes, spouses and the three best friends.[21]

For a more in-depth analysis, later on we restrict the sample to those individuals who have employed parents only: that is, an observation is included in the sample if and only if $E_{i,t-1}^{\textbf{Father, ongoing}} = 1$.

Using the occupations $O_{i,t}$, defined for both employed and unemployed individuals as explained in the Data subsection, we compute a new variable $S_{i,t}$, where S stands for "same" sector:

$$S_{i,t} = \begin{cases} 1 & \text{if } O_{i,t} = O_{i,t}^{\textbf{Father}} \\ 0 & \text{if } O_{i,t} \neq O_{i,t}^{\textbf{Father}} \\ \textit{missing} & \text{otherwise} \end{cases}$$

Such variable captures whether an unemployed individual is assumed to be (or not) seeking a job in the same sector of his employed father, or whether an individual is currently working (or not) in the same sector of his employed father.

We run regressions similar to those explained above, where the job finding events $J_{i,t}^f$ is regressed on the same sector indicator $S_{i,t}$. Notice that in this case the sample will include only those individual whose parents are employed, meaning that any correlation associated to $S_{i,t}$ will be *additional* to those obtained when looking at the correlation with the employed status of parents.

With the expection of our diff-in-diff specification, in all regressions described above we include individual-level fixed effects, in order to take out fixed individual characteristics that can be correlated with job market outcomes. Moreover, we cluster standard errors at the parents' level, because within-families correlations are likely to be important and to bias standard errors downwards if not properly accounted for.

In the Robustness section we question our empirical strategy, allowing for a more flexible specification; we show that our strategy yields the most "conservative" estimates, and we

[20]For instance the IQ, motivation, social skills or whatever other factors that are likely to be transmitted across generations and have an impact (directly or indirectly) on the performance in the labor market.

[21]Although we would like to run the same regressions for all these variables at the same time, the low amount of data for which all variables are available does not allow us to do so.

argue that what seems to be the most "obvious" approach leads to upward biased estimates of the marginal effects. Furthermore, the more flexible specification yields negligible gains in efficiency.

1.6 Results

1.6.1 Difference-in-Differences Estimation

	Dependent Variable		
	(1) Emp.Status	(2) Job Finding	(3) Job Separation
Father's emp. status (2m, lagged)	-0.00329	-0.0439	-0.000594
	(0.016)	(0.048)	(0.002)
Younger than 27	-0.0745***	-0.131**	0.00162
	(0.023)	(0.052)	(0.003)
Younger than 27*Father's emp. status (2m, lagged)	0.0822***	0.114**	-0.00253
	(0.023)	(0.049)	(0.003)
N	115823	7912	105727
R^2	0.066	0.040	0.006

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7. Difference-in-differences regressions of Employment Status, Job Finding and Job Separation. The control group is given by individuals aged at least 27. We report the coefficient of the **employment status of father**, of **belonging to the treatment group** and the **interaction term** (the effect we want to estimate). Standard errors are clustered at the father level. All regressions include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

In Table 1.7 we report the results of our diff-in-diff specification. The estimates indicate that having a father employed (rather than unemployed) increases in the individual employment rate of about 8 p.p.. We then decompose this result between an higher job finding rate and a lower job separation, simply by running the same regression changing the dependent variable. Column 2 and 3 of Table 1.7 shows that the bulk of the economic advantage lies in a much higher job finding rate (the effect estimates is 11 p.p.). We want to stress how the effects estimated by our regression are very large and significant. In section 1.6.2 we report the results of other linear probability models in which we control for individual unobserved heterogeneity[22].

[22] If we were to include individual fixed effects in the DD regressions, the identification of the father's effect would rely almost exclusively on cross-sectional variation, in the absence of a large number of individuals who happen to belong to both groups over their life-cycle. In other words, the DD specification would not work properly. On the other hand, the presence of individuals who belong to both the control and the treatment over their life-cycle can also create problems to the identification.

1.6.1.1 Other DD results

The results shown in the last section are perfectly consistent with our stylized model of intergenerational transmission of networks. Importantly, the estimates are robust to alternative definitions of the treatment group. In Table 11 (in Appendix 3.7), we run again the same regressions using years of potential experience in the labor market (years elapsed from completion of education), instead of age. The control group is defined as all the individuals with more than 10 years of potential experience. The results are virtually unchanged.

We also investigate whether the effect depends on individual characteristics such as age and education. In Table 12 (in Appendix 3.7), we estimate again the baseline regression adding a full set of interaction terms with a gender dummy (in column 1) and a college-education dummy (in column 2). The estimates indicate that the effect of the employments status of the father does not differ by gender, but instead it greatly diminishes when the individual has a college degree. This might reflect the fact that parents are more willing to help their offspring when the latter ones are more disadvantaged (for instance, less educated). Otherwise, this could also mean that the help received by college graduates lies in a better employment, rather than on the margin between employment and unemployment[23].

Finally, we do not find that the same results hold for mothers. Table 13 (in Appendix 3.7) shows that mothers are not useful work connections for their offspring: in particular, even though the effect on the employment status (column 1) is positive and significant, column 2 reveals that this effect does not arise through higher job finding rates. Therefore, the empirical evidence rejects that having the mother employed help the offspring find a job.

1.6.2 Job Finding Rate - Parental Links

In the remainder of the paper, we focus uniquely on the job finding rate since, as we show in the previous section, the differences in employment prospects of individuals by employment status of the father are mainly driven by differences in finding rates. Table 1.8 shows that having the father employed rather than unemployed has a strong and significant effect on the job finding rate of the offspring, perfectly in line with the results outlined above. The partial correlation observed in POLS models, including all relevant controls, lays in the region of 5-6 p.p. These effects are quite large (to be compared with a 12% in-sample average job finding rate) and robust to several model specifications. Panel regressions with RE yield a similar coefficient (6.4 p.p.). Importantly, the coefficient keeps the same size and it is estimated with

Nevertheless, we tried to run the regressions excluding such individuals from the sample and results (available upon request) are substantially unchanged.

[23]Among college graduates, the unemployment rate is just 3%.

a similar precision even in fixed effects models. This suggests that the effects captured by the coefficient do not depend on fixed factors (e.g. genes) that might be transmitted across generations. Notice that the in-sample average job finding rate is higher than the average job finding rate of the overall sample, consistent with the lower average age of the estimating sample. We estimate the baseline POLS regression separately by gender, finding that the father has a large and significant effect both on males and on females.

Conversely, mothers do not appear to have any significant effect on the job finding rate of offspring, neither for males nor for women. The coefficients are ranging between 3 and 4 p.p. but their estimates are less precise, even when we use the data as repeated cross-sections (Table 1.8, panel B).
As the employment status of couples is likely not to be independently distributed, our models might be suffering from omitted variable bias. In order to control for correlations between the employment status of the father and of the mother, we estimate the model including both regressors. The results shown in Table 1.8 (panel C) confirm the patterns shown in the separate regressions, yielding the father's employment status as the only important predictor of offspring's transitions. This is consistent with other studies as for instance Magruder (2010). The effect of having the father employed ranges between 7.6 and 11 p.p., while the effect of the mother is not stable across specifications and never significantly different from zero. This suggests that the positive effects of mother's employment status –shown in panel B of Table 1.8– were almost entirely driven by within-couple correlation in employment status. Notice that, even though standard errors rise in fixed effects estimation, the father's coefficient keeps having the same size (or even higher). This indicates that such effects do not depend on within-household correlation in employment status.
In order to get further insights on the father effects found so far, we test whether these are magnified when the occupational sectors of the offspring and of the father coincide. That is, we investigate whether individuals who search for a job in the same sector where their father is employed have additional advantages. As shown in Table 1.9, such additional advantages are estimated to be in the region of 4 p.p.[24]. The size of the coefficient is again robust to the inclusion of individual fixed effects. This is a substantial difference and it might be one of the main factors driving the occupational persistence across generations that we find in the data.

[24]This implies that having the father employed in the same sector where individuals are looking for jobs generates an effect that is at least 1.6 larger than having the father employed in some other sector. The effect found in Table 1.8 is a composition of the effect of fathers in the same sector and fathers in other sectors. For this reason, computing the additional effect as the ratio between the two estimates (0.4/0.6=0.66..) simply provides a lower bound.

Panel A	Dep. Variable: Job Finding				
	(1) POLS	(2) POLS (men)	(3) POLS(women)	(4) GLS	(5) FE
Emp. Status (father, lagged)	0.0643***	0.0559***	0.0965***	0.0645***	0.0566***
	(0.014)	(0.018)	(0.028)	(0.016)	(0.021)
Avg. Age (in-sample)	22.1	22.4	21.6	22.1	22.1
Avg. JF rate (in-sample)	0.120	0.114	0.131	0.120	0.120
N	7772	5051	2721	7772	7772
R^2	0.041	0.052	0.061		0.030
N of groups				753	753

Panel B	Dep. Variable: Job Finding				
	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. Status (mother, lagged)	0.0365**	0.0457*	0.0498	0.0365	0.0266
	(0.018)	(0.025)	(0.035)	(0.022)	(0.026)
Avg. Age (in-sample)	22.6	22.8	22.2	22.6	22.6
Avg. JF rate (in-sample)	0.123	0.118	0.131	0.123	0.123
N	7384	4640	2744	7384	7384
R^2	0.045	0.052	0.078		0.033
N of groups				703	703

Panel C	Dep. Variable: Job Finding				
	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. Status (Father, lagged)	0.0835***	0.0870***	0.110***	0.0921***	0.0764*
	(0.021)	(0.029)	(0.033)	(0.027)	(0.039)
Emp. Status (Mother, lagged)	-0.000429	-0.0192	0.0195	0.00135	-0.00587
	(0.024)	(0.036)	(0.037)	(0.034)	(0.041)
Avg. Age (in-sample)	22.1	22.3	21.8	22.1	22.1
Avg. JF rate (in-sample)	0.126	0.119	0.137	0.126	0.126
N	5420	3473	1947	5420	5420
R^2	0.047	0.062	0.082		0.037
N of groups				573	573

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.8. Linear regressions of Job Finding Rate (transition from Unemployed to Employed); coefficient for **employment status of father** and **mother** (1 for employed, 0 for unemployed), standard errors (clustered at the father level), average age and average job finding rate in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

	Dep. Variable: Job Finding		
	(1)	(2)	(3)
	POLS	GLS	FE
Emp. in Same Sector (father)	0.0422**	0.0447**	0.0407
	(0.018)	(0.021)	(0.026)
Avg. Age (in-sample)	22.0	22.0	22.0
Avg. JF rate (in-sample)	0.130	0.130	0.130
N	6257	6257	6257
R^2	0.045		0.031
N of groups		666	666

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.9. Regressions of Job Finding; coefficient for **father in same sector** (0 employed in other sector, 1 employed in same sector), standard errors (clustered at the father level), average age and average job finding rate in the sample of the regression. Model 1 is a pooled OLS regression, model 2 is a random effects GLS regression, model 3 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

We do not find any effects for mothers, consistently with our previous findings. Mothers' employment status does not appear to provide any advantages to offspring, not even when their job is similar to the one their offspring are looking for (the associated regression table is available upon request).

1.6.3 Job Finding Rate - Comparison with other strong Links

In this section we consider the employment status of the three closest friends and of the spouse, investigating whether these partial correlations are similar in magnitude to the parental ones we documented in the previous section. To ease the comparison we employ the same empirical strategy and model specifications. The only difference is that we do not distinguish between males and females in the regressions.

In the first model, we consider the number of employed friends[25], among the three closest as reported by individuals. Table 1.10 reveals that friends' employment status has a significant impact on the probability of transition from unemployment to employment. Having an additional employed (rather than unemployed) friend raises on average the individual job finding rate by 3 p.p. Notice that this coefficient is significantly smaller than the father's coefficient (about half in magnitude). Moreover, the friends' coefficient drops with the inclusion of fixed effects in the model, suggesting that individual characteristics are producing a bias in the baseline regressions. Some fixed factors are positively correlated with both the ability of

[25] We follow the same strategy as Cappellari & Tatsiramos (2011).

finding a job and having good (employed) friends. Our estimates are in line with those of Cappellari et al. (2010), who find an effect of about 7.4 p.p. on yearly transitions.

Panel A	Dep. Variable: Job Finding		
	(1)	(2)	(3)
	POLS	GLS	FE
Num. Employed Friends (lagged)	0.0287***	0.0275***	0.0110
	(0.003)	(0.005)	(0.008)
Avg. Age (in-sample)	33.5	33.5	33.5
Avg. JF rate (in-sample)	0.101	0.101	0.101
N	14127	14127	14127
R^2	0.028		0.031
N of groups		1919	1919

Panel B	Dep. Variable: Job Finding		
	(1)	(2)	(3)
	POLS	GLS	FE
Emp. Status (spouse, lagged)	0.0527***	0.0690***	0.0614***
	(0.010)	(0.015)	(0.022)
Avg. Age (in-sample)	43.3	43.3	43.3
Avg. JF rate (in-sample)	0.100	0.100	0.100
N	10580	10580	10580
R^2	0.027		0.021
N of groups		1075	1075

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.10. Regressions of Job Finding Rate (transition from Unemployed to Employed); coefficient for **number of employed friends** (from 0 to 3) **employment status of spouse** (0 or 1), standard errors (clustered at the individual level), average age and average job finding rate in the sample of the regression. Model 1 is a pooled OLS regression, model 2 is a random effects GLS regression, model 3 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

As Table 1.10 shows, spouse links seem to be stronger than those of friends. According to regression results, individuals whose spouse is employed experience a job finding rate that is 5-6 p.p. higher than that of individuals who are married to an unemployed spouse. One possible concern is assortative mating, i.e. the fact that people who are more likely to be employed tend to marry among them. However, the fact that the size of the estimated coefficient is robust to fixed effects estimation strategies suggests that this mechanism is not driving the results. Summing up, spouse effects are comparable in size to father's ones, while friendship ties seem to be a less important factor in the determination of the job finding rate.

1.7 Discussion

In this section we discuss our results and provide some possible alternative mechanisms that can explain the partial correlations observed in the data. The focus of our discussion is exclusively on the effects of fathers' variables on offspring' job finding rates, which we consider as the most important of our results. At a first glance, these positive effects are consistent with standard models of networks in the labor market (Calvó-Armengol & Jackson (2004)). Information flow on vacancies and job opportunities probably represents one of the main channels through which individuals belonging to the same social network help each other. Of course, the partial correlations uncovered by our regressions possibly include several other mechanisms.

Genetical and Human Capital Transmission

For instance, genetical and human capital transmission across generations might be driving the results. To this respect, we have to consider that for each of the models we estimate, we always include fixed effects as the last specification. In this way we capture fixed individual characteristics that have an effect on the dependent variable and are possibly correlated with the explanatory variables of interest [26]. Genetical endowments are an example of such individual characteristics that are properly controlled for in fixed effects models, assuming that their effect is linear and non time-varying. With respect to human capital, even though it could –at least in part– be assimilated to fixed factors in adult individuals, this is certainly not true for young individuals. Human capital is a time-varying factor that can be potentially relevant in our estimates. The presence of educational group dummies in our regression attenuates this problem, as education is a good proxy for human capital. However, if the effects were due to the transmission of human capital or work ethics, then we should find that the exact timing of the employment status (or the sectoral belonging) of the father does not matter much. Indeed, such transmission mechanisms are supposed to be long-lasting, and it is also reasonable to think that they take some time in order to produce their effects. Hence, as a further robustness check we include in our regression several lags of the employment status of the father. Interestingly, columns 1-4 of Table 1.11 reveals that

[26] To some extent, father's fixed effect might be better at capturing fixed characteristics that are transmitted across generations. Including such fixed effects in our regression -rather than individual ones- leaves the results unchanged.

only the contemporaneous employment status and sector of the father have an effect. The coefficient of the lags considered (3, 6 and 12 months) are actually negative or not significant, indicating that human capital transmission is not a relevant factor in our estimates. Since strong collinearity might be causing a bias in our coefficients, we also estimate a regression including only the 12-months lag of our variables of interest (columns 2 and 4 of Table 1.11). We find this to have, if anything, a slightly negative effect on the job finding rate. Repeating the same test for both the employment status and the occupational sector provides a test for, respectively, a general and an occupation-specific human capital interpretation. As we can see, the empirical evidence is strongly at odds with this interpretation. The fact that the coefficients of the current variables are even higher now reveals that in the baseline models these coefficients were picking up the negative correlations of the lagged variables, which are serially correlated.

Direct Hiring

Second, another possible channel is direct hiring of individuals by their father. Even though it is unclear whether this should be considered as an informational advantage or another kind of mechanism, we investigate whether a major part of the effects we find can be attributed to this channel. We study whether having a father who hires employees (rather than employee or self-employed without employees) boosts the advantages in terms of job finding rate. Column 5 of Table 1.11 shows that, if anything, having a father who is an employer has a negative effect on the individual job finding rate. This is strongly inconsistent with an interpretation of our results as direct hiring.

Local Labor Market Conditions

Another possibility is the existence of common shocks affecting both parental employment status and offspring' performances. For instance, if an individual and his father both live in a region that has experienced a positive shock, their employment statuses will be correlated as they will be caused by the same fundamental shock. Similar considerations can be made with respect to the occupational sector. If the partial correlations we find are due to local labor market conditions, then we should expect these correlations to be stronger when the offspring lives together with his father. To this purpose, we use the region of residence, generating a dummy that takes the value 1 when the region of residence of the offspring does not coincide

Dep. Variable: Job Finding

	(1) Lags	(2) Lag 12 only	(3) Sector lags	(4) Sector lag 12 only	(5) Fat. Hires Employees
Emp. Status (father, lagged)	0.0759*				0.0577***
	(0.041)				(0.019)
Emp. Status (father, 3 months lag)	-0.0275				
	(0.036)				
Emp. Status (father, 6 months lag)	-0.0238				
	(0.030)				
Emp. Status (father, 12 months lag)	0.00726	-0.0257			
	(0.025)	(0.024)			
Father in Same Sec. (lagged)			0.0790**		
			(0.040)		
Father in Same Sec. (3 mths lag)			0.00338		
			(0.051)		
Father in Same Sec. (6 mths lag)			-0.0197		
			(0.040)		
Father in Same Sec. (12 mths lag)			0.00691	-0.0117	
			(0.028)	(0.021)	
Father Hires Employees					-0.106
					(0.082)
N	6621	7648	4841	5855	8563
R^2	0.026	0.024	0.035	0.029	0.027
N of Groups	654	719	554	624	791

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11. Discussion: Human Capital and Direct Hiring. All regressions are fixed effects estimates. All regressions include all controls discussed in previous sections. Standard errors are clustered at the father level.

with the one of the father. Column 1 of Table 1.12 shows that the partial correlation of father's employment with offspring' job finding rate is instead magnified when the offspring lives in a different region from his father, even though the estimate of the difference is not very precise. In our regression we control for regional changes of offspring, to account for the possibility that individuals migrate in order to find a job, which would bias the estimate of the father's employment coefficients. Individuals who belong to different regions definitely belong to different local labor markets, and therefore we have to conclude that local labor market conditions are not an important driver of the correlations we find. In order to control further for local labor market conditions, we also compute the average unemployment rate by sector and by region. We then add these new variables to our regressions as additional controls. As shown in columns 2-5 of Table 1.12, the partial correlations are unchanged by the inclusion of all these possible controls. In particular, we are including dummies for the sector interacted with the year in column 4 and for the region interacted with the year in column 5, controlling for possible booms or busts of given segments of the labor market. Nonetheless, this does not appear to capture at all the effects outlined so far.

1.8 Robustness Checks

In this section we explore whether our results are robust to different choices of the sample and to different empirical strategies. First, we want to understand whether the composition of our sample might be driving our estimates. The fact that our estimating sample includes many individuals who are still at school or at the university might be creating problems of sample selection. To control for this possibility, we try to exclude individuals with a college degree from our sample. Column 1 of table 1.13 presents results of this estimation: although the size of the estimate is somewhat lowered, it still is statistically and economically significant, showing that college-educated individuals are not driving the bulk of the correlations we find.

Then, we consider the possibility that only very young workers (aged 16-20) are affected by the employment status of their father. However, when we include only individuals aged more than 20 years of age in the estimation (column 4), we maintain the size of the coefficient, despite losing more than one-third of our original sample.

Also, we consider the possibility that our assumptions on sectors of search might be important for our results: by using future and past occupations as proxies of current sectors of search, we are de facto excluding those individuals who are always unemployed in the BHPS, or who never report their occupation. To account for this possibility, we exclude controls for

Dep. Variable: Job Finding

	(1) Local Conditions	(2) Sector Unemp.	(3) Region Unemp.	(4) Sector*Year	(5) Region*Year
Emp. Status (father, lagged)	0.0558***	0.0553***	0.0553***	0.0564***	0.0542**
	(0.021)	(0.019)	(0.020)	(0.021)	(0.021)
Father emp. (in other region)	0.0619				
	(0.049)				
Father unemp. (in other region)	-0.121				
	(0.150)				
Has Changed Region from last year	X				
Unemployment of Sector		X			
Unemployment in Metropolitan Area of residence			X		
Interactions Sector $\times$ Year				X	
Interactions Region $\times$ Year					X
N	7816	8563	8563	8563	9246
R^2	0.029	0.027	0.029	0.047	0.062
N of Groups	754	791	791	791	828

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.12. Discussion: Local Labor Market Effects. All regressions are fixed effects estimates. All regressions include all controls discussed in previous sections. Standard errors are clustered at the father level.

	(1) No College	(2) No Sectors	(3) Different Model	(4) Age > 20
Emp. Status (father, lagged)	0.0461***	0.0490***		0.0616**
	(0.017)	(0.017)		(0.025)
Father U-E			0.172**	
			(0.072)	
Father E-U			0.0526	
			(0.057)	
Father E-E			0.0632***	
			(0.019)	
N	7826	9246	8644	5889
R^2	0.026	0.024	0.026	0.031
N of groups	671	828	792	576

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.13. Robustness Checks: regression without college graduates (column 1), no sectoral dummies (column 2), more flexible specification (column 3), Only individuals aged > 20 (column 4). Omitted category: Father U-U. All regressions are fixed effects estimates. All regressions include all controls discussed in previous sections. Standard errors are clustered at the father level.

occupation from our estimations. Results are reported in column 2: the coefficient is lowered by about 1 percentage point, maintaining statistical and economical significance.

Finally, we question our empirical strategy and consider the possibility that a more flexible model may allow us to better capture the nature of the correlations we find. That is, we do not keep only fathers who are on an ongoing spell but rather all the observations which are not missing. Specifically, we construct four indicators based on the two months of job history of the father during the offspring's transitions: hence we have one dummy for "father unemployed past month and current", one for "father unemployed past month but employed on current" and so on. Column 3 shows the results of such experiment: while the coefficient roughly corresponding to our empirical strategy (employed past month and current) maintains substantially the same magnitude and standard error, the coefficient corresponding to "father unemployed last month, employed today" is strikingly high. Such a coefficient is due to a relatively large number of transitions taking place at the same time (for both fathers and offspring) and does not correctly capture any direct effect of fathers on offspring. There are at least two main issues: first, common high-frequency shocks that we are not able to properly control for might be a common cause for these contemporaneous events. Second, there is the possibility that in fact offspring are affecting fathers (instead of the other way around), producing a large upward bias due to reverse causality.

1.9 Conclusion

We tested whether parental links affect labor market outcomes of individuals using rich panel data from the British Household Panel Survey. Our results indicate that, on average, those whose father is employed rather than unemployed experience an employment rate that is about 8 percentage points higher, with job finding rates which are higher by 5 percentage points and job separation rates which are lower by 0.3 p.p.. We also show that such difference is larger when individuals work in occupations similar to those of their father. We do not find similar correlations for mothers, and we show that father's effects are similar in magnitude, or larger, to those of other supposedly relevant links. We also document that the job separation rate is on average lower for individuals whose father is employed in similar occupations to theirs.

By means of a number of robustness checks, we show that our results are unlikely to be attributable to human capital transmission, to common shocks driving both outcomes at the same time or to the fact that fathers directly hire their offspring. Our conclusion is that parental networks are likely to play an important role in determining labor market outcomes.

Chapter 2

Like Father, Like Son: Occupational Choice, Intergenerational Persistence and Misallocation

2.1 Introduction

It is well known that a number of economic outcomes are correlated across generations, most notably income, education and occupational choice.[1] Such persistence is commonly believed to represent a failure of the equality of opportunity principle, besides being potentially symptomatic of an underlying misallocation of resources and talents (Mora 2009, Güell et al. 2015). In particular, a large degree of persistence in occupational choice may reflect the presence of barriers of various types in the labour market, implying a suboptimal allocation of workers to jobs. However, a quantitative theory of occupational persistence, that would help us understand whether or not persistence is indeed associated with inefficiencies, has not been developed yet.

In this paper, we study how intergenerational occupational persistence and labor misallocation are related. We demonstrate that when persistence stems from a number of sources, it is crucial to measure the quantitative importance of each and how they interact with one another. To do so, we develop a dynamic model of occupational choice and search frictions that features multiple channels of intergenerational transmission, and use it to decompose

[1] The first important contribution in the intergenerational literature was Becker & Tomes (1979); more recently, Solon (1992b), Solon (2002), Corak (2006b), Hertz (2006) and Björklund & Jäntti (2009) have documented persistence in income. For persistence in education, see Chevalier *et al.* (2009); and for occupational persistence, see Hout & Beller (2006), Constant & Zimmermann (2004), Escriche (2007), Eberharter (2008) and Dustmann (2004). Two reviews of the literature can be found in Black & Devereux (2010) and Ermisch *et al.* (2012).

the occupational persistence observed in UK data. Our model provides novel insights on the impact of different sources of persistence on the sorting of workers in the labor market, and therefore the aggregate level of efficiency and welfare.

To illustrate our main mechanism, we first develop a simple two–period model, in which both abilities and social contacts are transmitted across generations. We show that persistence can indeed be a sign of misallocation if parents help their offspring find a job faster in their current occupation, which is not necessarily where their offspring's comparative advantage lies. In our model, workers optimally choose their occupation, so that mismatch is not always detrimental to welfare. However, we find the equilibrium to generally be inefficient, as workers do not internalize that: i) search frictions interact with the level of mismatch present in the economy, and firms offer fewer jobs if they expect workers to be more mismatched and consequently less productive;[2] and ii) mismatch has dynamic effects, via intergenerational transmission. We also analytically establish that higher levels of persistence can be associated with either higher or lower welfare, depending on whether they are the result of stronger transmission of productivity or social contacts across generations.

To assess the quantitative importance of the different channels of persistence, we then extend our theory to a dynamic model that embeds a third channel of transmission (i.e. preferences)[3] and allows for mobility over the life–cycle. We investigate the quantitative importance of the three different forces in generating occupational persistence, and find that parental networks can account for about 78% of persistence, whereas transmission of comparative advantage and preferences account for 19% and 10%, respectively.[4] The very large role played by parental networks depends on the fact that they strongly interact with the other two factors generating persistence, thus acting as a multiplier. Moreover, we demonstrate that a model in which only productive abilities are transmitted across generations (which we call the *restricted model*) falls short in accounting for several key pieces of evidence and in general provides a much worse fit to the data.

The theory delivers two main predictions for agents who choose to pursue the same occupation as their parents (*occupational followers*) relative to those who do not (*occupational movers*). First, the former find jobs at a faster rate. Second, they earn lower wages. We find confirmation of both implications using data from the British Household Panel Survey (1991–2008) on male workers and their fathers. This dataset allows us to observe labor market transitions, occupational affiliation and wages of both fathers and sons, together

[2]This channel is present also in Bentolila *et al.* (2010b).

[3]Studies on intergenerational transmission of preferences and work attitudes include Dohmen *et al.* (2011), Paola (2013) and Bisin & Verdier (2005). Research on how these transmitted traits affect occupational choice includes Doepke & Zilibotti (2008), Caner & Okten (2010) and Escriche (2007).

[4]The sum of the effects of the three transmission channels exceeds 100% because they are endogenously correlated.

with a large number of other covariates.

We estimate that the degree of occupational persistence in the UK is substantial: at the 1–digit level, a worker is 72% more likely to be employed in a given occupation if his father is also currently employed in that occupation. When we test the model's predictions, we find that occupational followers exhibit monthly job–finding rates that are 5–6 p.p. higher than those of occupational movers. Given that the average in–sample job–finding rate is about 12.5 p.p., being in the same occupation as one's father yields a substantial advantage in terms of unemployment risk (robust to the inclusion of individual fixed effects). Regarding wages, we find that occupational followers exhibit large discounts (between 7 and 14 log points) relative to occupational movers. These results are shown to be robust to alternative definitions of the *occupational followers* group, using information on the entire labor market careers as well as only contemporaneous information. Finally, we also document that sons of high–wage fathers are more likely to be occupational followers, a fact that supports our theory, which is based on comparative advantage (rather than absolute advantage).

We calibrate the quantitative model in order to match the above–mentioned key pieces of empirical evidence, along with several other moments of the UK economy. In particular, the parameters governing intergenerational transmission are pinned down as follows: the parental networks transmission replicates the job–finding rate premium of followers, the comparative advantages replicates the differential in persistence by parental wage, and the preferences transmission is the residual channel of occupational persistence. We use the quantitative model to assess how each source of persistence affects welfare. When we shut down parental networks or the transmission of preferences, welfare improves. This is due to the improved (i.e. more aligned with productive advantages) allocation of workers to occupations: output per worker goes up, and firms react by posting more vacancies per worker than previously. In contrast, when we shut down the transmission of abilities, the reduction in persistence is accompanied by a reduction in welfare, driven by the inferior allocation of the workforce, which in turn also leads to less firm entry. However, the changes in welfare are relatively small, with a magnitude of 0.1% in consumption equivalent variation (CEV).

We also investigate the role of search frictions and find that the impact of parental networks on the allocation becomes negligible as frictions tend to zero; also, an increase in the severity of frictions in our model simultaneously generates a rise in the unemployment rate and a drop in labor productivity. Finally, in our model more generous unemployment benefits imply that workers are less likely to choose the same occupation as their father in order to reduce the probability of unemployment. This implies that, in addition to reducing occupational persistence, increasing benefits can potentially be welfare–improving, since the allocation of the workforce may also improve. Nonetheless, we find that an increase in unemployment benefits triggers a reallocation towards preferences rather than comparative advantages. Therefore, the overall effect on welfare is slightly negative. For instance, an increase in unemployment benefits of 25% yields a decrease in welfare of 0.3% (CEV). Importantly, the restricted model yields very different implications for this policy change by underestimating the negative welfare effects of increased benefits.

While there is a significant amount of research on income persistence across generations, work on occupational choice is far scarcer in the literature.[5] We contribute to this literature along several dimensions: First, we add to the empirical literature on occupational persistence across generations (Constant & Zimmermann 2004, Hellerstein & Morrill 2011, Ermisch & Francesconi 2002, Di Pietro & Urwin 2003, Long & Ferrie 2013) by documenting new facts on labor market outcomes of occupational followers. We show that, relative to other observationally equivalent workers, they find jobs faster but earn lower wages. Moreover, we provide new estimates of the likelihood of belonging to the same occupational category as one's father using contemporaneous information based on monthly transitions.

Second, our study bridges the literature on the determinants of occupational choice (Miller 1984; McCall 1991; Keane & Wolpin 1997; Papageorgiou 2014; Carrillo-Tudela & Visschers 2014), its consequences for inequality (Kambourov & Manovskii 2009) and unemployment duration (Wiczer 2014) and the literature on occupational persistence and career following (Laband & Lentz 1983). Our paper is one of the few to adopt a theoretical and quantitative perspective on occupational choice across generations,[6] thus providing novel insights into how persistence maps to efficiency and aggregate welfare.

Third, we relate to the literature on social networks in the labor market (for instance, see Horváth 2014 and Galenianos 2014b)[7] and particularly the transmission of contacts or related advantages across generations (Corak & Piraino 2011b, Kramarz & Skans 2014b, Pellizzari *et al.* 2011, Lentz & Laband 1989 and Aina & Nicoletti 2014). Fourth, our paper investigates the possibility of misallocation of the labor force due to socially suboptimal occupational choice, as in Bentolila *et al.* (2010b), Celik (2015), Hsieh *et al.* (2013) and Munshi & Rosenzweig (2016). Finally, the decomposition exercise undertaken here is very close in spirit to those of income persistence across generations, such as Restuccia & Urrutia (2004), Lee & Seshadri (2014), Abbott *et al.* (2013) and Gayle *et al.* (2015).

[5]The economic literature has primarily focused on the study of income, while the sociological literature, pioneered by Blau & Duncan (1967), has focused on occupational persistence. More recent contributions include Stier & Grusky (1990), Checchi (1997) and Andres *et al.* (1999).

[6]In this sense, the closest paper to ours is Sinha (2014), who studies how borrowing constraints affect occupational choices and how this mechanism can be important in understanding persistence in developing countries.

[7]Other contributions include Granovetter (1973b), Montgomery (1991b), Calvó-Armengol & Jackson (2007), Pellizzari (2010b), Cingano & Rosolia (2012), Hensvik & Skans (2013), Topa (2001b) and Dustmann *et al.* (forthcoming).

The rest of the paper is organized as follows: Section 2 develops a two–period model of occupational choice and intergenerational transmission. Section 3 presents empirical evidence on occupational persistence. Section 4 outlines the dynamic quantitative model, which is calibrated and used for counterfactual experiments in Section 5. Finally, Section 6 concludes.

2.2 A Simple Two–Period Model

The model is based on Bentolila *et al.* (2010b), which is a static version of the standard search model à la Diamond-Mortensen–Pissarides. We add the following features to their framework: i) overlapping generations that are connected to each other; ii) a notion of occupational persistence across generations; and iii) two different sources of persistence across generations.

The economy is populated by a measure 2 of risk–neutral individuals who live for two periods (a young and an old phase of life). The population has the typical OLG structure, with each young individual being connected to one old individual (who we call "his father"). There are two occupations denoted by $j \in \{A, B\}$, each of which corresponds to a separate labor market. The only choice made by individuals is in which occupation to search for a job.

In each of the two markets, matches between unemployed workers and vacancies take place according to a matching function $M(U_j, V_j)$, where U_j represents the total number of search efficiency units, and V_j is the number of vacancies in the market. We define the probability of finding a job for an unemployed worker exerting 1 unit of search efficiency as $p(\theta_j) = \frac{M(U_j,V_j)}{U_j}$, where $\theta_j = \frac{V_j}{U_j}$ represents the labor market tightness. Conversely, $q(\theta_j) = \frac{M(U_j,V_j)}{V_j}$ represents the job-filling rate (probability of a firm meeting a worker).

Upon matching, the generated surplus is split according to Generalized Nash Bargaining, where the worker's bargaining power is equal to β. If unmatched, workers receive an unemployment benefit (normalized to 0 without loss of generality). We assume that search takes place during the young phase, while production takes place only during the old phase.[8] As a result, equilibrium wages are equal to a share β of the worker's productivity.

Workers are heterogeneous in their occupation–specific productive advantage and in the endowment of social contacts. A worker without productive advantage produces y, whereas he produces $(1+a)y$ when he can exploit his productive advantage, where $a > 0$. We assume that there exist two types of workers, with $\tau = \{A, B\}$ denoting the occupation in which each type has his productive advantage.[9] Types are transmitted across generations according

[8]These assumptions are made for simplicity, since they make the model static.

[9]We could allow the comparative advantage to vary, depending on the occupation chosen by the worker, and this would not

to the following transition probabilities: $P(\tau = A|\tau^F = A) = P(\tau = B|\tau^F = B) = \rho$ (we denote the father's variables with an F superscript), with $\rho \in [0, 1]$. Due to the symmetry of the transition matrix, the long–run distribution is characterized by $P(\tau = A) = P(\tau = B) = \frac{1}{2}$, so that types are independent if $\rho = \frac{1}{2}$. In what follows, we assume that $\rho > \frac{1}{2}$, that is an individual has a tendency to be of the same type as his father, on average. Importantly, in this framework there is no productive *absolute* advantage. This is consistent with Papageorgiou (2014) who argues that comparative advantage is the most important component in occupational choice.

Social contacts are occupation–specific and help individuals find jobs by increasing the efficiency units of search. We assume that young individuals have more social contacts in their father's occupation: one possible interpretation is that they can exploit their father's networks if they decide to enter the same occupation. Without loss of generality, we normalize the network of young workers who do not search in the same occupation as their father to zero. Thus, their efficiency units of search are equal to $1 + \tilde{n}$, where $\tilde{n}$ represents the size of the network they can exploit. We further assume that all workers, when passing from the young to the old phase, accumulate a network of size N with probability μ and of size n otherwise, with $\mu \in [0, 1]$. To sum up:

$$\tilde{n} = \begin{cases} 0 & \text{if } o \neq o^F \\ N & \text{if } o = o^F \qquad \text{w.p.} \qquad \mu \\ n & \text{if } o = o^F \qquad \text{w.p.} \quad (1-\mu) \end{cases}$$

where o denotes the occupation chosen, and o^F denotes the father's occupation. Finally, we also assume that $n < a < N$ (Assumption A), in order to induce different groups of workers to make different occupational choices.

2.2.1 Equilibrium characterization

We focus on steady state symmetric equilibria, given that the two markets have the same fundamentals.[10] In equilibrium, each market attracts a measure 1 of workers, with an identical composition of labor productivity and contacts endowment. In order to facilitate the exposition, we will sometimes frame the discussion using occupation A, given that the same results hold for occupation B.

alter the qualitative predictions of the model. The crucial assumption underlying our results is that ability types change more slowly than contacts.

[10] Thanks to the symmetry of the equilibrium, we will frequently use the following property: $P(A|B) = P(B|A)$ whenever A and B are events defined over the distribution of types and occupations (which have equal mass in equilibrium).

There is a subset of workers in this economy for which the occupational choice is trivial. In other words, all those workers whose productive advantage lies in their father's occupation will simply choose that occupation. We calculate their mass as follows:[11]

$$\begin{aligned} P(\tau = A|o^F = A) =& P(\tau = A|o^F = A; \tau^F = A)P(\tau^F = A|o^F = A) + \\ & P(\tau = A|o^F = A; \tau^F = B)P(\tau^F = B|o^F = A), \end{aligned} \tag{2.1}$$

where o^F denotes the father's occupation. Noting that type transmission does not depend on the occupational affiliation of the father, and after defining $P(o^F = A|\tau^F = A) = m$ (an endogenous object yet to be determined), we can simplify the previous expression to the following:

$$P(\tau = A|o^F = A) = \rho m + (1-\rho)(1-m) \equiv \Psi(m), \tag{2.2}$$

where we have used the fact that $P(\tau^F = A|o^F = A) = P(o^F = A|\tau^F = A)$. Here, $(1-m)$ is a measure of the *productive mismatch* in the economy, i.e. how poor the sorting between workers and occupations is along the productivity dimension. If $m = 1$, the occupational choice is perfectly aligned with the type, that is, all workers of a given type enter the same occupation, which is where they are most productive. Moreover, $\Psi(m)$ denotes the mass of young workers who do not face any tradeoff in their occupational decision.

In order to solve for the equilibrium m, we first look at the optimal occupational choice of the workers who face the tradeoff. These are the workers whose productive advantage lies in one occupation but whose father (and his social contacts) is employed in the other. For instance, consider those for whom $\tau = A$ and $o^F = B$. They will optimally choose occupation A if and only if:

$$p(\theta)\beta(1+a)y \geq p(\theta)(1+\tilde{n})\beta y, \tag{2.3}$$

where a higher wage in occupation A, namely $(\beta(1+a)y)$, more than compensates for the higher job–finding rate in occupation B, namely $(p(\theta)(1+\tilde{n}))$. It is easy to see that, under Assumption A, Condition (2.3) holds only for those workers endowed with a small network. All the others (whose mass is μ) optimally decide not to pursue their productive advantage.

We now look at the total probability that type A chooses occupation A:

$$P(o = A|\tau = A) = \Psi(m) + (1-\mu)(1-\Psi(m)), \tag{2.4}$$

where we have rewritten the total probability that type A chooses occupation A as a weighted

[11] In the analysis, we will frequently use the Law of Total Probability: $P(A|C) = \sum_n P(A|B_n)P(B_n|C)$, where $\{B_n : n = 1, 2, 3, ...\}$ is a partition of the sample space.

average of the probability of him choosing occupation A when he has a tradeoff and when he does not. In the first case, he chooses A with probability 1 and in the second case, with probability $(1 - \mu)$. The expression in (2.2) must equal the share of old workers of type A in occupation A (which we previously defined as m) in steady state. Equating the two yields:

$$m^* = \frac{1 - \mu\rho}{1 + \mu(1 - 2\rho)}. \tag{2.5}$$

Lemma 1. *The degree of sorting of workers according to their productive advantage, m^*, is decreasing in μ and increasing in ρ.*

Proof. See Appendix. □

There are two extreme cases: $m^* = 1$ when $\mu = 0$ (no one's choice depends on contacts) and $m^* = \frac{1}{2}$ when $\mu = 1$ (everyone follows in their father's footsteps, regardless of their type). In general, m^* is decreasing in μ and increasing in ρ. The former effect is straightforward to demonstrate: the higher is μ, the more workers will choose purely according to contacts, which availability needs not be aligned with productivity. In contrast, the reason for the latter effect is that, as ρ increases, the pool of workers who choose the same occupation as their father (which is the pool of workers using social contacts) increasingly coincides with the pool of workers who would have chosen that occupation even without social contacts. In this sense, an increase in the persistence of productive types across generations attenuates the negative effects of the use of contacts on worker sorting. As a result, the allocation of the workforce improves. In the limit case when $\rho = 1$, the allocation of workers is no longer affected by μ and there is no mismatch in the economy.

It is useful to derive an expression for the equilibrium value of Ψ, by substituting equation (2.5) into (2.2):

$$\Psi^* = \frac{\rho + \mu - 2\rho\mu}{1 + \mu(1 - 2\rho)}. \tag{2.6}$$

Lemma 2. *The share of workers who do not face any tradeoff in their occupational choice, Ψ^*, is decreasing in μ and increasing in ρ.*

Proof. See Appendix. □

An increase in μ, in equilibrium, triggers an increase in the share of workers who choose their occupation according to the availability of contacts. In turn, this lowers Ψ, as more young workers will face a tradeoff. Conversely, an increase in ρ improves the alignment of contacts and comparative advantage, by means of an increase in m^*.

In order to close the model, we now consider the entry of firms. Free entry implies that firms will post vacancies up to the point at which the expected profits from doing so are exactly equal to the fixed cost κ. In order to evaluate profits, firms need to form an expectation of worker productivity in the market. Define $\gamma(m)$ as the probability with which, upon matching, the firm meets with a high–productivity type. This probability will differ from m, since different workers exert different efficiency units of search.

Define the total efficiency units of search as U:

$$\begin{aligned} U(m) &= \Psi(m)[(1-\mu)(1+n)+\mu(1+N)] + (1-\Psi(m))[(1-\mu)+\mu(1+N)] = \\ &= 1+\mu N+\Psi(m)(1-\mu)n. \end{aligned} \tag{2.7}$$

The previous expression is composed of four terms. The former two represent the efficiency units of search exerted by those workers who do not face a tradeoff and can therefore exploit their network, which can be either small or large. The latter two represent the units of search exerted by those with a tradeoff. A proportion $(1-\mu)$ of them decide to stay in the occupation in which they have a comparative advantage, thus giving up their contacts. The remaining share μ decide not to pursue their comparative advantage and to exploit their large network of contacts. This latter group is the only one for which the type and the occupation chosen in equilibrium are not aligned.

Thus, a firm meets with high–productivity type with probability:

$$\gamma(m) = 1 - \frac{(1-\Psi(m))\mu(1+N)}{U(m)}. \tag{2.8}$$

This expression is in fact the relevant dimension of *mismatch* for aggregate outcomes, that is how poor the allocation of workers is perceived to be by firms. In general, it can be shown that $\gamma(m) < m$ for $\mu > 0$. This is because mismatched workers are overrepresented in the unemployment pool, thus displacing more productive workers. It turns out that an increase in μ has a negative effect on $\gamma(m)$ for two reasons, since not only does it increase the number of mismatched workers, it also increases their probability of being drawn by a firm. On the other hand, ρ has a positive effect on $\gamma(m)$: it reduces the number of those workers with a tradeoff (by raising $\Psi(m)$), and it raises the total efficiency units of search (through the effect on $\Psi(m)$, see Equation 2.7).

Lemma 3. *The probability of meeting with a productive type in the pool of the unemployed, γ^*, is decreasing in μ and increasing in ρ.*

Proof. See Appendix. □

We now look at the free entry condition. In equilibrium, the expected profits of firms must equate the fixed cost of posting a vacancy:

$$q(\theta)(1-\beta)(1+\gamma(m)a)=\kappa. \tag{2.9}$$

This shows that equilibrium tightness closely depends on $\gamma(m)$, the likelihood of a firm matching with a high–productivity type. This implies that any factor which affects $\gamma(m)$, will also affect equilibrium tightness in the same direction. This reflects the fact that firms react to changes in the average labor productivity of the economy. For instance, a decrease in $\gamma(m)$ reduces the expected profits from a match and therefore reduces incentives for firm entry. As a result, equilibrium tightness declines. In other words, the fact that some workers decide not to pursue their comparative advantage generates externalities on the demand side, such that aggregate variables are eventually also affected.

Lemma 4. *The equilibrium labor market tightness, θ^*, is decreasing in μ and increasing in ρ.*

Proof. See Appendix. □

2.2.2 Occupational Followers vs. Occupational Movers

In this section, we derive empirical predictions for the workers who decide to enter the same occupation as their fathers.

We first derive an expression for the degree of occupational persistence across generations in the economy. Such an expression will be useful in the calculations that follow:

$$\begin{aligned} P(o=A|o^F=A)=&P(o=A|o^F=A;\tau=A)P(\tau=A|o^F=A)+ \\ &P(o=A|o^F=A;\tau=B)P(\tau=B|o^F=A)= \\ &=\Psi(m)+\mu(1-\Psi(m))\equiv\mathcal{P}(m). \end{aligned} \tag{2.10}$$

We denote as $\mathcal{P}(m)$ the degree of intergenerational occupational persistence, that is, the probability of a young worker choosing the same occupation as his father. We define π as an individual dummy that takes the value 1 if the worker is in the same occupation as his father and 0 otherwise. The model allows us to derive predictions for *occupational followers* (for whom $\pi=1$) and *occupational movers* (for whom $\pi=0$). We first consider the probability of finding a job, which is equal to the product of $p(\theta)$ and the efficiency units of search exerted, denoted by s. Occupational followers can exploit their social contacts and therefore will have higher units of search than occupational movers. Thus,

$$E(s|\pi = 1) = m^{\pi}(1 + N) + (1 - m^{\pi})[\mu(1 + N) + (1 - \mu)(1 + n)] > 1 = E(s|\pi = 0). \quad (2.11)$$

Note that, among occupational followers, some workers will be mismatched (their mass is m^{π}, an endogenous object that we solve for below). These workers necessarily must have exploited large networks, and thus their efficiency units of search are $(1+N)$ with probability 1; otherwise, they would not have given up their comparative advantage. On the other hand, the non–mismatched workers may have either large or small networks, with probability μ and $(1 - \mu)$ respectively. In any case, each subgroup's total efficiency units of search exceed 1. As a result, the job–finding rate of occupational followers will be strictly higher than that of occupational movers.

In order to discuss wages in the model, we first need to derive expressions for the probability of being a productive type, for both followers and movers. In other words, we need to solve for m^{π}:

$$\begin{aligned} m^{\pi} \equiv P(\tau = A|o = A; o^F = A) =& \frac{P(\tau = A; o = A; o^F = A)}{P(o = A; o^F = A)} = \\ =& \frac{P(o = A|\tau = A; o^F = A)P(\tau = A; o^F = A)}{P(o = A; o^F = A)} = \\ =& \frac{\Psi(m)}{\mathcal{P}(m)} = \frac{\Psi(m)}{\Psi(m) + \mu(1 - \Psi(m))}, \end{aligned} \quad (2.12)$$

where we have used $\frac{P(\tau=A;o^F=A)}{P(o=A;o^F=A)} = \frac{P(\tau=A|o^F=A)}{P(o=A|o^F=A)}$. We define $(1 - m^{\pi})$ as the *mismatch among occupational followers*. If $\mu > 0$, then m^{π} is strictly smaller than one: the very fact that some workers base their occupational choice on contacts induces some mismatch in the economy. It is easy to verify that repeating the same calculations for the occupational movers shows that there is no mismatch in their case, i.e. $P(\tau = A|o = A; o^F = B) = 1$. This is because, by construction, those workers who do not choose the same occupation as their fathers are not using contacts and therefore they necessarily must have based their decision on productive advantage.

Conditional on matching, the probability of meeting with a high–productivity type among occupational followers is as follows:

$$\gamma^{\pi}(m^{\pi}) = 1 - \frac{(1 - m^{\pi})(1 + N)\mathcal{P}(m)}{U^{\pi}(m^{\pi})}, \quad (2.13)$$

where $U^{\pi}(m^{\pi})$ is the total efficiency units exerted by occupational followers:

$$U^{\pi}(m^{\pi}) = \mathcal{P}(m)[m^{\pi}(\mu(1+N)+(1-\mu)(1+n))+(1-m^{\pi})(1+N)].$$

This equation consists of three terms: the first two represent the efficiency units of search exerted by the occupational followers who are not mismatched and are using either a large or small network, while the last term, in contrast, represents the mismatched workers, who are necessarily using a large network.

We can now derive the expected wages for the two groups:

$$E(w|\pi=1) = \beta(1+\gamma^{\pi}(m^{\pi})a)y < \beta(1+a)y = E(w|\pi=0). \tag{2.14}$$

For $\mu > 0$, we have $\gamma^{\pi}(m^{\pi}) < 1$, and therefore the wages of occupational movers are, on average, strictly higher than the wages of occupational followers. The two predictions derived so far are summarized in the following statement.

Empirical Prediction 1. *Workers who choose the same occupation as their father have, on average, higher job–finding rates and lower wages. Moreover, the former effect is predicted to survive the inclusion of controls for the fixed productive type, while the latter is not:*

1. $E(JF|o=o^F) > E(JF|o \neq o^F)$.
2. $E(w|o=o^F) < E(w|o \neq o^F)$.
3. $E(JF|o=o^F; o=\tilde{o}; \tau=\tilde{\tau}) > E(JF|o \neq o^F; o=\tilde{o}; \tau=\tilde{\tau}) \quad$ *with* $\tilde{o}, \tilde{\tau} \in \{A, B\}$.
4. $E(w|o=o^F; o=\tilde{o}; \tau=\tilde{\tau}) = E(w|o \neq o^F; o=\tilde{o}; \tau=\tilde{\tau}) \quad$ *with* $\tilde{o}, \tilde{\tau} \in \{A, B\}$.

The intuition behind this result is straightforward. The presence of the father in the same occupation increases the son's available amount of social contacts, thus increasing his job–finding rate. This occurs regardless of the worker's type or occupation. On the other hand, the differences in wages are driven only by selection of workers. In particular, all mismatched workers happen to be occupational followers. However, once we control for the occupational choice and the fixed type (that is, his productivity level), wages are no longer affected by the father's presence.

Another key prediction of the model is that wages are correlated across generations. In this economy, only two wage levels are offered in equilibrium: $\beta(1+a)y$ to the non–mismatched workers and βy to the mismatched workers. We show that having a mismatched father increases the probability that the son will be mismatched as well. Define $\bar{w}$ as a dummy that takes the value 1 if the worker is non–mismatched (that is, he is a potential high earner), and 0 otherwise. The probability of being a high earner, conditional on having a high–wage father, is as follows (the derivation is reported in the Appendix):

$$P(\bar{w} = 1|\bar{w}^F = 1) = \rho + (1 - \mu)(1 - \rho). \tag{2.15}$$

Symmetrically, one can also show that:

$$P(\bar{w} = 1|\bar{w}^F = 0) = (1 - \rho) + (1 - \mu)\rho. \tag{2.16}$$

It is easy to verify that $P(\bar{w} = 1|\bar{w}^F = 1) > P(\bar{w} = 1|\bar{w}^F = 0)$ for $\mu > 0$. In words, having a high–earning father increases the chances of being a high–earning worker. As a result, wages are correlated across generations.

Empirical Prediction 2. *Wages are correlated across generations. Sons of high–earning (low–earning) fathers are more likely to be high earners (low earners) themselves.*

Remarkably, this result does not hinge on any transmission of efficiency level (i.e., unidimensional productivity) across generations, as is usually assumed in the literature. In our case, the transmission of wages across generations is a byproduct of the *transmission of mismatch* across generations.

2.2.3 Occupational Persistence and Mismatch

In this section, we examine how changes in the structural parameters of the economy (ρ and μ) affect occupational persistence across generations. We also shed light on the relationship between occupational persistence and productive mismatch.

In this economy, occupational persistence is brought about through two different channels: use of contacts and transmission of type (comparative advantage). Strengthening either of these two channels (by increasing μ or ρ, respectively) increases persistence.

Proposition 1. *The probability that a young worker chooses his father's occupation, $\mathcal{P}^*$, is strictly increasing in both μ and ρ.*

Proof. See Appendix. □

In order to understand the comparative statics exercise behind Proposition 1, let us first write an expression for the equilibrium level of persistence, evaluating equation (2.10) at equilibrium:

$$\mathcal{P}(m^*) = \mu + (1 - \mu)\Psi(m^*). \tag{2.17}$$

An increase in μ has a twofold effect on persistence: on the one hand, it increases the share of workers who base their occupational choice on contacts; on the other hand, it decreases the share of workers who do not face any tradeoff. These two effects work in opposite directions, but it turns out that the former is always stronger than the latter.

In constrast, an increase in ρ affects persistence only by way of Ψ^*. In particular, a higher probability of transmission of type improves the overall allocation of workers and therefore reduces the probability of facing a tradeoff. Thus, occupational persistence also increases.

We now look more in depth at the relationship between occupational persistence and mismatch. We derive an equation relating the overall level of mismatch in the economy to the mismatch among occupational followers and the degree of occupational persistence:

$$\begin{aligned} m =& P(\tau = A | o = A; o^F = A)\mathcal{P}(m) + P(\tau = A | o = A; o^F = A)(1 - \mathcal{P}(m)) = \\ =& m^\pi \mathcal{P}(m) + (1 - \mathcal{P}(m)). \end{aligned} \tag{2.18}$$

Thus, overall mismatch can be rewritten as a weighted average of the mismatch among occupational followers and that among occupational movers. Plugging equation (2.10) into (2.18) and evaluating it in equilibrium yields:

$$m^* = \Psi(m^*) + (1 - \mathcal{P}(m^*)). \tag{2.19}$$

An implication of (2.19) is that $(1 - m^*) \leq \mathcal{P}(m^*)$, i.e. the degree of mismatch in the economy is bounded above by the degree of occupational persistence. This is due to the fact that only occupational followers can be mismatched in equilibrium.[12]

2.2.4 Constrained Efficiency

We now turn to the efficiency properties of our model economy. Inefficiency of the Search Equilibrium (SE hereafter) arises in our setup for two distinct reasons: First, the economy suffers from the usual inefficiency typical of the random search framework. Secondly, the equilibrium level of mismatch does not need to correspond to the efficient level. These two sources of inefficiency are independent of one another, and we describe them below sequentially. We start with the latter, since it is a characteristic feature of our setup, while the former applies to many other search models.

[12] This depends on the fact that if a worker is mismatched, it is because he is using social contacts, and this is something that only occupational followers can do. If we were to relax the assumption that social contacts only work through parents, this would no longer be the case. For instance, we could allow workers to have social contacts in the occupation that is not their father's. As long as the probability of having social contacts is higher in their father's occupation, all of our results would still hold.

2.2.4.1 Optimal Level of Mismatch and Occupational Persistence

There are three reasons why the occupational choices of workers (and therefore, the level of productive mismatch) may not be aligned to those of a social planner (SP hereafter): a) workers do not internalize the detrimental effects of the level of mismatch on the equilibrium tightness; b) workers do not internalize that the mismatch has *dynamic* effects via the intergenerational distribution, since the shares of workers with/without a tradeoff (Ψ, in the notation of the SE) depend on the level of mismatch; and c) workers do not internalize the vacancy costs that have to be paid to transform search efficiency units into actual matches.

The externalities described in (a) are not faced by the SP, since he is not constrained by the free entry condition, and can therefore fix the preferred levels of mismatch and tightness independently.[13] Hence, we specify the SP's problem without any reference to this channel, so that the tightness θ is treated as if it were an exogenous parameter, with the understanding that the SP can also operate on this margin.

Since the occupational choice of each subgroup of workers (i.e., combinations of productive types, large/small networks, mismatched/non–mismatched father) affects the equilibrium allocation differently, we allow the SP to choose different degrees of mismatch across groups. Thus, beyond the general level of sorting m, we also define $\{m_1, ...m_8\} \in [0,1]^8$ as the sorting of each subgroup. For instance, m_1 represents the share of workers sorted along their comparative advantage among those with a well–sorted father, the same productive type as their father and a large network (see Appendix for a complete description of the groups). The welfare function to be maximized by the SP is as follows:

$$\begin{aligned}
\mathcal{W}^{\mathcal{SP}}(m_1,...,m_8) = 2\Big\{ & m\rho\mu[p(\theta)y(1+m_1a)-\kappa\theta](1+m_1N) \\
+ \quad & m\rho(1-\mu)[p(\theta)y(1+m_2a)-\kappa\theta](1+m_2n) \\
+ \quad & m(1-\rho)\mu[p(\theta)y(1+m_3a)-\kappa\theta](1+(1-m_3)N) \\
+ \quad & m(1-\rho)(1-\mu)[p(\theta)y(1+m_4a)-\kappa\theta](1+(1-m_4)n) \\
+ \quad & (1-m)\rho\mu[p(\theta)y(1+m_5a)-\kappa\theta](1+(1-m_5)N) \\
+ \quad & (1-m)\rho(1-\mu)[p(\theta)y(1+m_6a)-\kappa\theta](1+(1-m_6)n) \\
+ \quad & (1-m)(1-\rho)\mu[p(\theta)y(1+m_7a)-\kappa\theta](1+m_7N) \\
+ \quad & (1-m)(1-\rho)(1-\mu)[p(\theta)y(1+m_8a)-\kappa\theta](1+m_8n)\Big\},
\end{aligned} \tag{2.20}$$

where m, which is the total share of workers who realize their comparative advantage, is a

[13] It is true that, if workers were aware of the fact that equilibrium tightness depends on the level of mismatch, there would be less mismatch. However, at the same time, this margin is simply ignored by the SP. As a consequence, (a) does not represent a reason for the SP to produce less mismatch than in the SE.

strictly increasing function of $\{m_1, ...m_8\}$ (see Appendix). It is straightforward to show that the SP indeed cares about the consequences of occupational allocation on future generations, via intergenerational transmission. In other words, he internalizes the fact that the share of each subgroup is a function of m (channel (b) described above).[14]

The total derivative of $\mathcal{W}^{\mathcal{SP}}$ w.r.t. the sorting of any of these groups is composed of two different terms:

$$\frac{d\mathcal{W}^{\mathcal{SP}}}{dm_j} = \underbrace{\frac{\partial\mathcal{W}^{\mathcal{SP}}}{\partial m}\frac{\partial m}{\partial m_j}}_{reallocation\ effect} + \underbrace{\frac{\partial\mathcal{W}^{\mathcal{SP}}}{\partial m_j}}_{inner\ effect} \qquad \forall\, j \in \{1, ..., 8\}. \tag{2.21}$$

The *reallocation effect* has to do with the intergenerational distribution. In other words, the SP understands that the equilibrium shares depend on the allocation. The *inner effect*, though it involves a similar tradeoff as the one faced by workers, includes the additional consideration of the vacancy costs. In general, both of these effects depend on all the elements of the vector $\vec{m} = \{m_1, ...m_8\}$ and it is not easy to fully characterize the SP's equilibrium. Instead, we derive conditions under which the SE allocation is not efficient (see the Appendix for details).

Define $N^* = \frac{N}{1+N} - \frac{N}{1+N}\frac{\kappa\theta}{p(\theta)y}$ and $n^* = \frac{n}{1-n} - \frac{n}{1-n}\frac{\kappa\theta}{p(\theta)y}$.

Proposition 2. *Depending on the parameter values, the SE allocation $\vec{m}^{SE}$ does not necessarily coincide with the efficient one.*

- *Under $a > N^*$ and $a > n^*$:*
  The SP wants to achieve less mismatch than in the SE.

- *Under $a < N^*$ and $a < n^*$, $\exists\bar{\rho} > \frac{1}{2}$ such that $\forall\rho < \bar{\rho}$:*
  The SP wants to achieve more mismatch than in the SE.

Proof. See the Appendix. □

Intuitively, high values of N and n, along with low values of a and κ, and ρ arbitrarily close to $\frac{1}{2}$, can drive the SP to choose even more mismatch than in the SE. In this case, the benefits from using better search technology more than offset the costs (i.e. a drop in labor productivity) for the economy as a whole.

Another implication of Proposition 2 is that, in general, the level of occupational persistence in the SE is not socially optimal.[15]

[14] For instance, the share of subgroup 1 (whose allocation is described by the m_1 variable) is a function of the mismatch of the parent generation, as well as of the transmission parameters ($m\rho\mu$). In Equation 2.20, we are considering a steady–state allocation (in which the mismatch of both generations is the same).

[15] Occupational persistence is a function of the allocation of workers $\{m_1, ...m_8\}$ (see the Appendix for details).

2.2.4.2 Optimal Level of Tightness

We now turn to the optimal level of labor market tightness in the economy. We define $\mathcal{W}^{\mathcal{SE}}$ as the welfare achieved by the SE, which corresponds to aggregate net income, that is, the difference between expected match output and the vacancy cost multiplied by the total number of search efficiency units in the economy:

$$\mathcal{W}^{\mathcal{SE}} = 2[p(\theta)(1+\gamma a)y - \kappa\theta]U. \tag{2.22}$$

We take the level of γ and U, which are endogenous variables that depend on the level of m, as given. It is easy to show that the equilibrium level of θ is generally inefficient, unless we are in a knife–edge case. In particular, the derivative of welfare with respect to market tightness is as follows:

$$\frac{\partial \mathcal{W}^{\mathcal{SE}}}{\partial \theta} = 2\kappa \left[\frac{\eta_V(\theta) - (1-\beta)}{1-\beta}\right] U. \tag{2.23}$$

where we have used the fact that $q(\theta)(1+\gamma a)y = \frac{\kappa}{1-\beta}$ and the definition $p(\theta) = q(\theta)\theta$, and where $\eta_V(\theta) = \frac{q'(\theta)\theta + q(\theta)}{q(\theta)}$ is the elasticity of the matching function with respect to V. Generally, $\eta_V(\theta)$ will differ from $(1-\beta)$, thus making the equilibrium inefficient.[16]

2.2.4.3 Occupational Persistence and Welfare

In this section, we establish the relationship between occupational persistence and welfare. The former is an endogenous object, and therefore we first need to understand how welfare is affected by changes in the determinants of persistence (that is, the parameters μ and ρ). Changes in μ or ρ have, in principle, an ambiguous effect on welfare. More specifically, each of them affects three different variables simultaneously: the total amount of efficiency units of search U, the sorting of workers across occupations γ and the level of tightness θ. The total derivative of welfare with respect to μ is as follows:

$$\frac{d\mathcal{W}}{d\mu} = \frac{\partial \mathcal{W}}{\partial \mu} + \frac{\partial \mathcal{W}}{\partial \theta}\frac{d\theta}{d\mu}. \tag{2.24}$$

The second term reflects the externalities mentioned in the previous sections, whereby variation in the average level of labor productivity transmits to the equilibrium level of tightness ($\frac{\partial\theta}{\partial\mu} < 0$). Whether this increases (decreases) welfare depends on whether the equilibrium level of tightness is inefficiently low (high).

With respect to the first term (the direct effect), it can itself be decomposed into two

[16] This is the same inefficiency studied by Hosios (1990), which arises from a combination of search externalities and Nash bargaining with pre–fixed shares of surplus division.

different margins:

$$\frac{\partial \mathcal{W}}{\partial \mu} = 2\left[p(\theta)(1+\gamma a)y - \kappa\theta\right]\frac{\partial U}{\partial \mu} + 2p(\theta)ayU\frac{\partial \gamma}{\partial \mu}. \tag{2.25}$$

The first term is always positive, reflecting the improvement in the search technology of the economy ($\frac{\partial U}{\partial \mu} > 0$). The second term, on the other hand, is always negative, reflecting that it is now harder for firms to match with productive types ($\frac{\partial \gamma}{\partial \mu} < 0$). The overall effect is ambiguous, depending on the specific parametrization.

Turning to the effect of ρ, the same decomposition can be performed:

$$\frac{d\mathcal{W}}{d\rho} = \frac{\partial \mathcal{W}}{\partial \mu} + \frac{\partial \mathcal{W}}{\partial \theta}\frac{d\theta}{d\rho}. \tag{2.26}$$

The aforementied considerations apply here as well. One important difference is that here the effect of ρ on market tightness is positive ($\frac{\partial \theta}{\partial \rho} > 0$). Moreover, the direct effect (i.e. the first term) is now unambiguously positive:

$$\frac{\partial \mathcal{W}}{\partial \rho} = 2\left[p(\theta)(1+\gamma a)y - \kappa\theta\right]\frac{\partial U}{\partial \rho} + 2p(\theta)ayU\frac{\partial \gamma}{\partial \rho}. \tag{2.27}$$

Not only does an increase in ρ inflate the efficiency units of search (since $\frac{\partial U}{\partial \rho} > 0$) through an increase in occupational persistence, but it also enhances the sorting of workers ($\frac{\partial \gamma}{\partial \rho} > 0$).

An implication of the discussion so far is that, in general, there is no one–to–one relationship between occupational persistence and welfare.

Proposition 3. *Changes in the degree of occupational persistence, $\mathcal{P}$, can be associated with either an increase or a decrease in the level of welfare, $\mathcal{W}$. If $\eta_V(\theta) \geq (1-\beta)$ and $\frac{N}{n} \leq \hat{N}$, (where $\hat{N} = f(\mu, \rho, n)$, see Appendix), then:*

- *An increase (decrease) in persistence generated by an increase (decrease) in μ has negative (positive) effects on welfare: $\frac{\partial \mathcal{P}}{\partial \mu} > 0$ and $\frac{\partial \mathcal{W}}{\partial \mu} \leq 0$.*
- *An increase (decrease) in persistence generated by an increase (decrease) in ρ has positive (negative) effects on welfare: $\frac{\partial \mathcal{P}}{\partial \rho} > 0$ and $\frac{\partial \mathcal{W}}{\partial \rho} \geq 0$.*

Proof. See the Appendix. □

In other words, it is crucial to understand the extent to which the different channels are generating persistence. For instance, if the latter is entirely due to the transmission of the productive type, then it is not a sign of a suboptimal allocation of workers into occupations.

If, instead, persistence is brought about by workers choosing according to the avilability of their father's contacts, then it may be a signal of underlying mismatch.

In this sense, it is unclear whether occupational persistence across generations is socially desirable, unless we are able to decompose it into its sources. In order to answer this question, in Section 4 we will construct a structural model of intergenerational transmission and occupational choice, so that in Section 5 we will be able to perform a decomposition exercise.

2.3 Empirical Evidence

In this section, we document the degree of occupational persistence across generations in the UK and test the key predictions (Empirical Prediction 1) of the model developed in the previous section. To this end, we use the British Household Panel Survey (BHPS) and in particular the dataset constructed by Lo Bello & Morchio (2013).

2.3.1 The Data

The BHPS is a yearly survey taken by about 10,000 individuals per year in the UK. It was first carried out in 1991, and the last available wave for this study is 2008. The survey is characterized by a fairly high follow–up rate, with more than 90% of the individuals being interviewed also in the subsequent year, and a number of new households entering the sample each year. In total, 32,377 individuals were interviewed in the BHPS during the period 1991-2008. We restrict our sample to males[17] aged 16–65, and are left with 12,982 individuals, for a total of 1,023,888 monthly observations. Individuals report a detailed job history of the previous year, including all the employment/unemployment spells, along with several job characteristics of each job (among them, the occupational group). In this way, we are able to construct long labor market histories for each individual (potentially up to 216 months) and, more importantly, we are able to observe transitions at the monthly frequency. Apart from a detailed job history, each individual provides demographic information, including gender, age, education, occupation, race, marital status, region of residence, etc. One key feature of the dataset is that it allows us to connect individuals to their fathers and to track them both over time.

The job–finding rate is defined as the monthly probability of transiting from unemploy-

[17] We exclude women from the sample for several reasons: i) employment rates of men and women are substantially different (especially for the parent generations); ii) in order to maintain comparability to the rest of the literature, which also excludes women; iii) in previous work we found that, although occupational following is also prevalent among women, there is no evidence that mothers serve as network providers (see Lo Bello & Morchio 2013).

ment to employment. Wages are calculated by dividing the total monthly labor income by the number of hours normally worked per week multiplied by four (the information on hours worked is only available for the current job at the moment of the interview, that is, it is recorded annually).

2.3.2 Intergenerational Occupational Persistence

The data allows us to study the extent of occupational persistence across generations. We compute the distribution of workers across occupations and study the probability of a father and his son belonging to the same occupational group. In order to account for the unequal distribution of workers across occupations, we construct likelihood ratios. For the sake of concreteness, we define the *persistence index* $\mathcal{P}_j$ as the ratio between the probability of belonging to a given occupation j conditional on the father also belonging to it and the unconditional probability of belonging to occupation j:

$$\mathcal{P}_j = \frac{P(o = j|o^F = j)}{P(o = j)} .$$

We define nine occupational groups, following the SOC aggregation by major group (the 1–digit level), as established by the Employment Department Group and the Office of Population Censuses and Surveys. Results are shown in Table 2.1:

Occupational group	**Likelihood Ratio**
Managers & Administrators	1.29
Professional	2.60
Associate Professional & Technical	1.62
Clerical & Secretarial	1.26
Craft & Related	1.55
Personal & Protective Service	1.58
Sales	1.34
Plant & Machine	1.94
Agriculture & Elementary	2.67
Average (unweighted)	1.76
Average (weighted)	1.72

Table 2.1. Occupational Persistence Indexes (Likelihood Ratios). Source: BHPS (1991–2008).

We find a large degree of occupational persistence. The estimated likelihood ratios of occupational persistence are greater than 1, indicating that a worker is more likely to belong to a given occupation if his father also belongs to it. The average likelihood ratio is estimated to be 1.76, implying that an individual is 76% more likely to be in a given occupation if his father is as well (this excess probability ranges from 29% to 167%, depending on occupation).

Interestingly, persistence does not appear to vary systematically with the occupation's skill level or wage.[18] Repeating the same exercise at the 2–digit level, we find that the average unweighted and weighted likelihood ratios are 5.69 and 4.71, respectively (see Table 16 in the Appendix).

Part of the persistence might be explained by the usual socioeconomic variables, such as age, education or the region of residence. In order to account for this, we estimate linear probability models which regress the probability of belonging to a given occupation (as opposed to any other) on a number of covariates. We estimate the model for each occupation, and present the results in Table 15 (in the Appendix). The estimates reveal that a worker is *ceteris paribus* 1.59 and 15.1 p.p. more likely to belong to the same occupation as his father. These are large probability differences and are highly statistically significant in all of the 9 occupations.

We also perform some addditional checks in order to investigate whether occupational persistence is primarily related to regional factors. For instance, living in a poor region (or a region with a limited variety of job opportunities) might mechanically increase the likelihood ratio. In that case, we would not be comparing the conditional probability to the *correct* unconditional probability. We plot the region–specific weighted average likelihood ratio against the average regional wage and a measure of occupational concentration (the Herfindahl index), and find that neither of these two dimensions can predict persistence (results are shown in Figures 11 and 12 in the Appendix,). This provides reassurance that regional factors are not playing a major role in determining the results.[19]

2.3.3 Intergenerational Occupational Persistence and Occupational Attachment

Thus far, we have shown that a worker's occupational affiliation tends to be highly correlated with that of his father. In this section, we investigate whether this phenomenon is persistent over the life–cycle. This is important because young workers, who are potentially sampling different occupations, may be those who are driving the likelihood ratios estimated in the previous section. More importantly, these young workers might be using their father's occupation as a stepping stone to their eventual occupation (possibly to avoid unemployment). If this is the case, then occupational persistence would be a short–run phenomenon, with

[18] This seems to suggest that borrowing constraints are not playing a major role in occupational choice. We also checked whether likelihood ratios vary by father's income within an occupational group. Our results show that occupational persistence decreases only slightly. For instance, if we only consider the top 1/3 of earners in each of the occupations, the average likelihood ratio drops to 1.61 (Table 17 in the Appendix).

[19] An important caveat is that we only have 19 regions. It is plausible that the relevant level for the father–son transmission is finer than that. However, the sample size does not allow us to estimate occupation–specific indexes of persistence at the regional level.

limited consequences for the allocation of workers to occupations.

First, we document that likelihood ratios are not decreasing over the life–cycle. For instance, the average (unweighted) likelihood ratio is 1.88 for workers younger than 20, as opposed to 1.91 for workers aged 25–30 and 2.03 for workers older than 30 (see Table 18 in the Appendix).

Second, we look at the length of the occupational spells of followers, as opposed to those of movers. The average occupational tenure is 2.16 years for followers, and 1.73 years for movers.[20] This is true also for occupations chosen very early in an individual's career. Figure 2.1 plots the share of workers still in their first occupation against the number of years of labor market experience, for followers and movers separately.

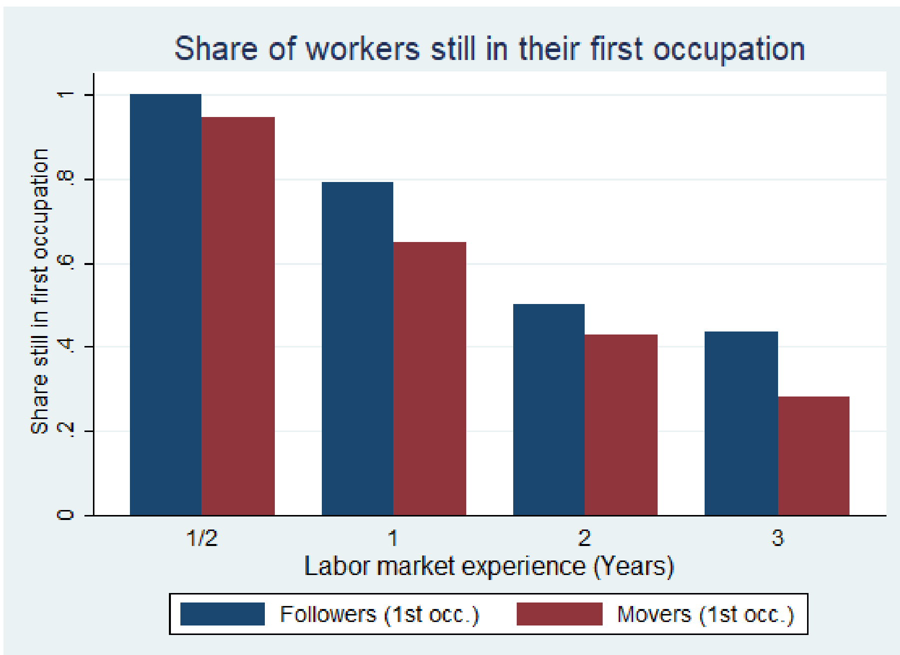

Figure 2.1. Share of workers still in their first occupation, by years of labor market experience. Source: BHPS (1991–2008).

We can see that a worker who starts his career in the same occupation as his father's is substantially less likely to exhibit occupational mobility. For instance, after two years from the start of their first employment spell, 60% of occupational followers will not have changed occupation[21] as compared to 49% of occupational movers. At the same time, these statistics reveal a large degree of *hysteresis* in occupational transitions. In other words, the initial

[20]When we restrict our attention only to the spells that we observe from the start, we find again that followers tend to be more attached to their occupation (average tenure of 1.84 years versus 1.69 years).

[21]In Figure 2.1, we do not count flows back into the original occupation as *still in the same occupation*. If we were to do that, we would find a slightly larger difference between followers and movers.

occupation is a good predictor of occupational affiliation even several years after the start of the employment spell. In this sense, the father's influence on the initial occupational choice may have long–lasting consequences for his son's outcomes and the aggregate allocation.

As an additional piece of evidence, we look at whether the contemporaneous presence of the father in the same occupation has an impact on the probability of changing occupation. To this end, we run the following regression:

$$OC_{i,t} = \alpha + \beta\pi_{i,t-1} + \boldsymbol{\gamma}\boldsymbol{X}_{i,t} + \epsilon_{i,t}, \tag{2.28}$$

where $OC_{i,t}$ is a dummy taking the value 1 if the occupation at time t is different from the one at $t-1$ (i.e. there has been an occupational switch[22]) and 0 otherwise; $\pi_{i,t}$ is a dummy variable that takes the value 1 if the occupation of son i and his father coincide at time t, and 0 otherwise; $\boldsymbol{X}_{i,t}$ is a vector of control variables that include a third degree age polynomial, dummies for educational categories and occupational groups (observed for the employed, imputed for the unemployed), marital status, ethnic group, smoking behavior (to capture health level), region of residence and quarter dummies; $\epsilon_{i,t}$ is the idiosyncratic error term.

We estimate Equation 2.29 with pooled OLS, random effects and fixed effects, with the estimates of β shown in Table 2.2.

Dependent Variable: Occupational Change

	(1) POLS	(2) RE	(3) FE
Father in same occupation ($\pi_{i,t-1}$)	-0.00811***	-0.00794***	-0.00872***
	(0.002)	(0.002)	(0.002)
Average in–sample OC rate	0.0265	0.0265	0.0265
N	53208	53208	53208
R^2	0.015	-	0.014
Number of pairs	-	938	938

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.2. Regressions of Occupational Change (transition from one occupation to another); coefficient for **father in same occupation last month** (dummy variable), standard errors and average occupational change rate in the regression sample. Model 1 is a pooled OLS regression, model 2 is a random effects GLS regression, and model 3 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behavior, marital status, ethnicity, quarter and occupation of employment. Source: BHPS (1991–2008).

We find that if the father is employed in the same occupation, there is a substantial reduction in the likelihood of changing occupation. The estimated impact is in the region of -0.8/0.9 p.p., which represents about one–third of the average in–sample monthly occu-

[22]The occupational switch can take place either through unemployment (where we compare the previous and subsequent occupations) or not (direct employment–to–employment switch).

pational change rate (2.65 p.p.). One possible interpretation is that some workers are more mobile than others in general, and therefore they will happen to be less often in the same occupation as their father, thus mechanically generating a correlation between the two variables. However, notice that: i) we are exploiting the exact timing of the transitions (using the lagged persistence variable), thus making this interpretation less likely; ii) in Column 3, we are controlling for individual fixed effects, ruling out this type of explanation. The estimated coefficient, which is quite stable across specifications, suggests that a worker is more reluctant to leave his father's occupation, even on top of any unobserved fixed heterogeneity.

In the following subsections, we turn to testing the two main predictions of the model, namely that occupational followers[23] have, on average, higher job–finding rates but lower wages.

2.3.4 Occupational Persistence and Job–Finding Rates

The first prediction of the model is that *occupational followers*, i.e. sons who are in the same occupation as their father, will on average have a higher job–finding rate. Given that we observe employment status and occupational affiliation, we can directly test this prediction. Therefore, we run the following regression:

$$JF_{i,t} = \alpha + \beta\pi_{i,t} + \boldsymbol{\gamma}\boldsymbol{X}_{i,t} + \epsilon_{i,t}, \tag{2.29}$$

where $JF_{i,t}$ is defined only for the unemployed and takes the value 1 if a job is found at time t and 0 otherwise; $\pi_{i,t}$ is a dummy variable that takes the value 1 if the occupation of son i and his father coincide at time t and 0 otherwise;[24] $\boldsymbol{X}_{i,t}$ is a vector of control variables that include a third–degree age polynomial, dummies for educational categories and occupational groups (observed for the employed, imputed for the unemployed), marital status, ethnic group, smoking behavior (to capture health level), region of residence and quarter dummies; $\epsilon_{i,t}$ is the idiosyncratic error term.

We estimate Equation 2.29 with pooled OLS, random effects and fixed effects, and present the estimates of β shown in Table 2.3:

We find that *occupational followers* have, on average, a substantially higher monthly job–finding rate (+5.4 p.p.) relative to *occupational movers*. Given that the unconditional probability of finding a job is estimated to be 12.5%, an individual whose father is in the

[23] Our working definition of *occupational follower* is based on $\pi_{i,t}$. However, the following results for JF rates and wages hold for more stringent definitions of *occupational follower* (for instance, starting the spell as a follower and then staying there for at least 6 or 12 months).

[24] The occupation of an unemployed individual is assumed to be the one in which a job will be found at the end of the unemployment spell. Moreover, this variable is defined only for those with an employed father.

Dependent Variable: Job–Finding Rate

	(1) POLS	(2) RE	(3) FE
Father in same occupation ($\pi_{i,t}$)	0.0546^{***}	0.0531^{**}	0.0546^{**}
	(0.016)	(0.021)	(0.026)
Average in–sample JF	0.125	0.125	0.125
N	4142	4142	4142
R^2	0.057	-	0.046
Number of pairs	-	401	401

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3. Regressions of Job–Finding Rate (transition from Unemployed to Employed); coefficient for **father in same occupation** (dummy variable), standard errors and average job–finding rate in the regression sample. Model 1 is a pooled OLS regression, model 2 is a random effects GLS regression, and model 3 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behavior, marital status, ethnicity, quarter, and occupation of search/employment. Source: BHPS (1991–2008).

same occupation increases his monthly probability of finding employment by about 42%. Importantly, the effect is robust to the inclusion of individual fixed effects (column 3), which control for unobserved heterogeneity across individuals. The identification of individual fixed effects is made possible by the panel structure of the data. The coefficient presented in column (3) of Table 2.3 is estimated by exploiting the variation in π (i.e. whether or not the father is in the same occupation), *within* the son's working life. This is in line with our model, which predicts that even after controlling for occupation and fixed type (τ), the father's occupation is still an important determinant of the individual's job–finding rate. We also find that these effects are robust to the exclusion of the self–employed from the sample (see Table 19 in the Appendix).

To the extent that social networks are slowly accumulated over time (as will be the case in our quantitative model), we also look at whether the impact of the father's occupation changes with his occupational tenure. Consistent with the prediction of the theory, we obtain a positive (though not statistically significant) coefficient for the interaction between $\pi_{i,t}$ and father's tenure, as shown in Table 20 in the Appendix.

Finally, we examine whether the impact of $\pi_{i,t}$ changes with age. We find that the effect is particularly high (up to +12 p.p.) among the youngest workers and then monotonically declines thereafter (Figure 13 in the Appendix). This piece of evidence lends support to our interpretation: young workers, who lack experience in the market, are expected to depend more heavily on their father's contacts. In a dynamic setting, like that to be developed in Section 2.4, workers accumulate contacts themselves, and therefore the influence of their father will fade over time.

2.3.5 Occupational Persistence and Wages

The second key prediction of the model is that *occupational followers* have lower wages on average, which according to the model is entirely due to selection. In fact, upon choosing an occupation, the wage only depends on the individual's productivity level in that occupation. That is, the father's occupational affiliation no longer matters. Thus, the difference between *occupational followers* and *occupational movers* is predicted to disappear after controlling for individual fixed effects (which capture the productivity level).

In order to test this hypothesis, we construct for each individual an index of how long he spent in the same occupation as his father during his working life. We do this for two reasons: first, we want to construct groups that do not change over the life–cycle of individuals; and second, it is generally unclear whether we should look at the father's occupation at the moment of the wage observation or at the start of the job spell.[25] Thus, we define q_i as the fraction of his months in employment that individual i spent in the same occupation as his father:

$$q_i = \frac{\sum\limits_t \pi_{i,t}}{\sum\limits_t E_{i,t}}, \tag{2.30}$$

where $E_{i,t}$ is a dummy taking the value 1 if the individual is employed in period t and 0 otherwise. The index q_i ranges from 0 to 1, and is a measure of the number of months (out of those in which he was employed) during which his occupation coincided with his father's. In Figure 2.2, we plot the wage profiles of three groups: those for which $q_i = 0$, $q_i \geq 0.5$ and $q_i = 1$.

We can see that the wages of those who spent more time in the same occupation as their father are lower by up to 20% on average throughout their entire working life. Remarkably, this difference appears to be constant over the lifecycle.

We investigate whether these differences depend on observable heterogeneity across workers. In particular, we estimate the following regressions:

$$\log(w_{i,t}) = \alpha + \beta q_i + \boldsymbol{\gamma} \boldsymbol{X}_{i,t} + \epsilon_{i,t}, \tag{2.31}$$

where $\log(w_{i,t})$ is the natural logarithm of the wage (observed at the annual frequency); q_i is defined in (2.30); $\boldsymbol{X}_{i,t}$ is a vector of control variables; and $\epsilon_{i,t}$ is the idiosyncratic error term.

We estimate Equation 2.31 by POLS and RE. Given that controlling for unobserved heterogeneity is not possible in this regression model, we estimate the same regression again

[25] In the Appendix (Figure 14), we show that differences in wages are robust to alternative definitions of *occupational followers*.

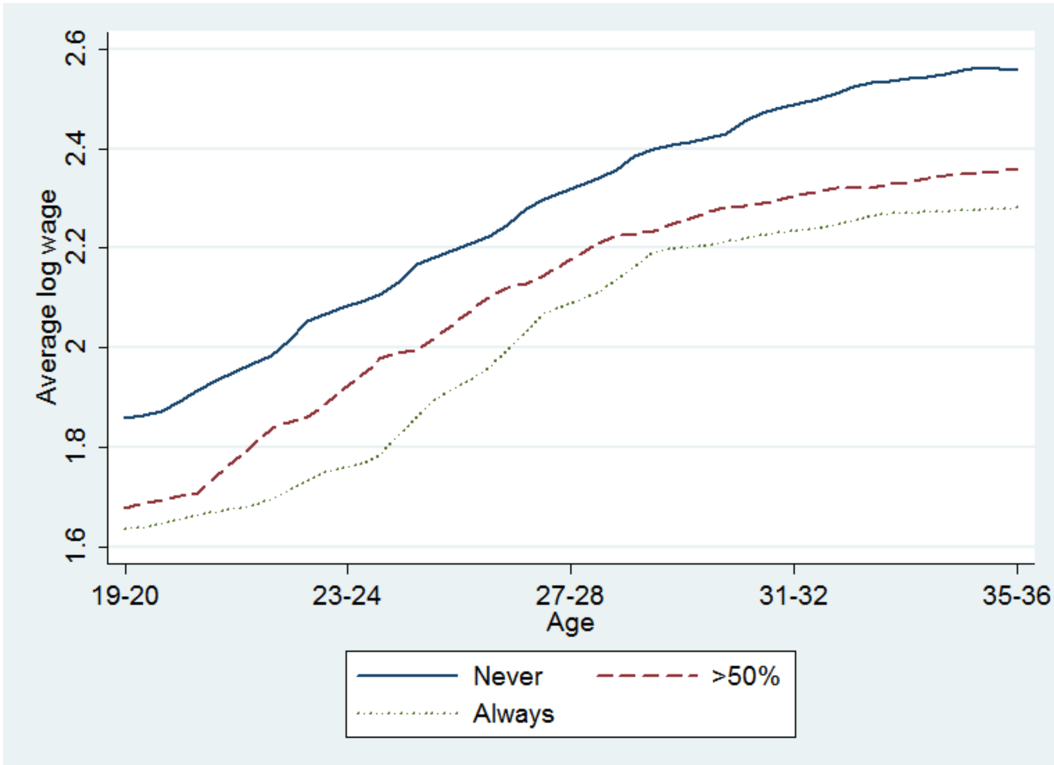

Figure 2.2. Wage profiles by proportion of employed worklife spent in the same occupation as the father. Source: BHPS (1991–2008).

except that we replace the independent variable q_i with $\pi_{i,t}$, the time–specific persistency dummy variable:

$$\log(w_{i,t}) = \alpha + \beta\pi_{i,t} + \boldsymbol{\gamma}\boldsymbol{X}_{i,t} + \epsilon_{i,t}. \tag{2.32}$$

The first two columns of Table 2.4 indicate that individuals who have spent more time in the same occupation as their father tend to earn lower wages, even after adding all the controls. We find that those who spend 10% more of their employed working life in the same occupation as their father earn 1.45%–1.52% lower wages, on average. Columns 3 to 5 present the estimates of β in Equation (2.32). We find an average discount of 7.6% associated with the presence of the father in the same occupation. However, this effect declines to 2.4% (which is barely statistically significant at the 90% confidence level) when we allow for RE in the regression model, and is reduced even further (to the point that it is neither statistically nor economically significant) when individual fixed effects are included in the regression. Overall, these results lend strong support to our theory.

In the Appendix (Table 21), we show that these results are robust to trimming the sample (i.e. removing the top and bottom 1% or 5% of the wage observations).

Dependent Variable: Log Hourly Wage

	(1) POLS	(2) RE	(3) POLS	(4) RE	(5) FE
Share of time in same occ. as father (q_i)	-0.145***	-0.152***			
	(0.017)	(0.035)			
Father in same occ. ($\pi_{i,t}$)			-0.076***	-0.024*	-0.0003
			(0.014)	(0.013)	(0.014)
N	6485	6485	4776	4776	4776
R^2	0.623	-	0.604	-	0.624
Number of pairs	-	922	-	850	850

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4. Regressions of Log Hourly Wage; coefficient for **share of time spent in same occupation as father** (from 0 to 1), standard errors and **father in same occupation** (dummy variable). Models 1 and 3 are pooled OLS regressions, models 2 and 4 are random effects GLS regressions, and model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education and occupation, second–order polynomials in occupational tenure and potential labor market experience, firm size, region of residence, smoking behavior, marital status, ethnicity, and year. Source: BHPS (1991–2008).

2.3.6 Unemployment Risk and Wages

We have so far established that occupational followers: i) tend to spend less time in unemployment; and ii) tend to earn lower wages. However suggestive, these two pieces of evidence *per se* do not imply that individuals actually face the tradeoff (between employment prospects and wages) described in our model. For instance, it could be that these two observations are the results of looking at two different subsamples (the unemployed and the employed), which may differ in other characteristics as well.

In order to overcome this issue, we exploit the entire working life of the workers in the sample. For each worker i, we compute the share of time spent employed $\bar{E}_i = \frac{\sum_t E_{i,t}}{\sum_t E_{i,t}+U_{i,t}}$ (a measure of his employment prospects) and the average monthly wage[26] earned throughout his working life $\bar{W}_i$ (a measure of lifetime labor earnings). In order to compute these lifetime statistics, we include observations from age 25 onwards.[27]

We find that $\bar{E}_i$ is positively related to q_i, while the opposite is true for $\bar{W}_i$ (Figure 2.3). Occupational followers appear to be characterized by better employment prospects and lower wages.

[26]This measure incorporates the unemployment risk margin as well. We construct it in the following manner: first, for each year, we multiply the monthly wage by the number of months that the individual is employed; we then sum them over the years; and finally, we divide the total by the number of wage observations (to correct for the unbalanced nature of the panel).

[27]The rationale behind this is to ensure that we are not capturing effects related to variation in the age of entry into the labor market.

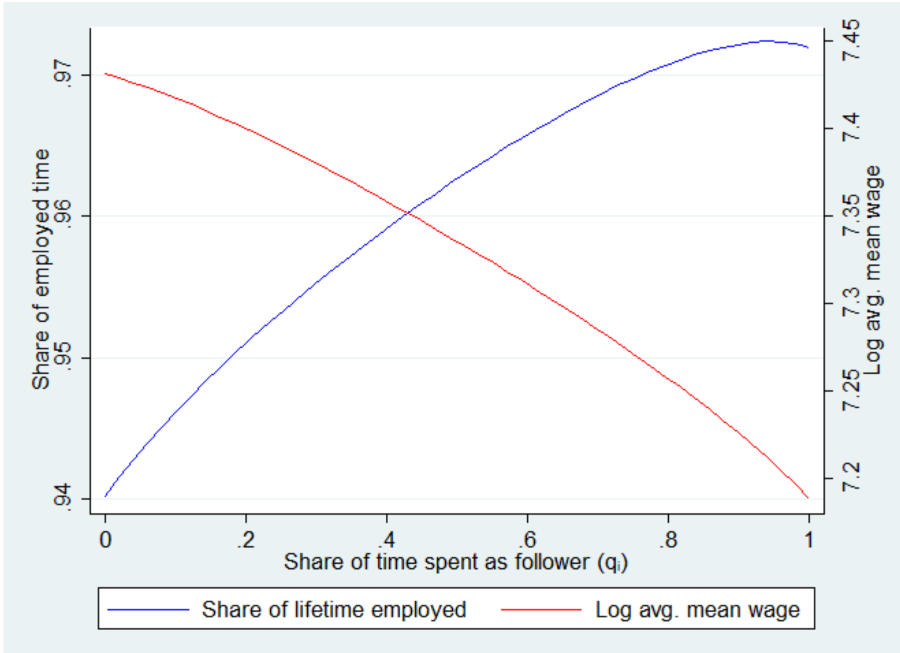

Figure 2.3. Locally weighted linear polynomial regression (degree 1, bandwidth 0.5) of share of lifetime employed and log average mean wage against the share of time spent as a follower. Source: BHPS (1991–2008).

In Table 2.5, we show the residual partial correlation between the aforementioned variables, controlling for fixed characteristics of individuals (i.e. education and race). Column 1 and 2 deliver the same message as Figure 2.3: occupational followers tend to have lower wages (by up to -24%) but better employment prospects (on average, they are employed for 5.2 p.p. more of their total time spent in the labor force). Interestingly, employment prospects and wages are generally positively correlated (Column 3), but their respective correlations with q_i have opposite signs. The sign of both of these correlations is robust to the introduction of the other control variables. In other words, conditional on lifetime employment prospects, followers tend to have lower wages (Column 4); and conditional on the average lifetime wage, tend to spend more time employed (Column 5).

Overall, the empirical evidence presented here is consistent with the tradeoff featured in our simple model, strongly suggesting that workers indeed face such a tradeoff.

2.3.7 Absolute vs. Comparative Advantage

One of the key findings presented above, namely the wage discount of *occupational followers*, may also be consistent with theories of occupational sorting based on absolute advantage, such as Groes *et al.* (2014). According to this alternative view, sons of high–wage fathers

	Dependent Variable				
	(1)	(2)	(3)	(4)	(5)
	$\bar{W}_i$	$\bar{E}_i$	$\bar{E}_i$	$\bar{W}_i$	$\bar{E}_i$
Share of time in same occ. as father (q_i)	-0.239***	0.0526**		-0.290***	0.0514***
	(0.069)	(0.025)		(0.061)	(0.014)
Log avg. mean wage ($\bar{W}_i$)			0.103***		0.108***
			(0.009)		(0.009)
Share of litefime employed ($\bar{E}_i$)				2.006***	
				(0.169)	
Controls (educ, race)	X	X	X	X	X
N	524	601	524	524	524
R^2	0.064	0.014	0.209	0.267	0.228

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5. Regressions of log average mean wage ($\bar{W}_i$) and share of lifetime spent employed ($\bar{E}_i$); coefficient for **share of time spent in same occupation as father** (from 0 to 1), log average mean wage and share of lifetime spent employed; standard errors in parentheses. All models include dummies for education and ethnicity. Source: BHPS (1991–2008).

tend to be high–ability workers themselves and therefore they may be more prone to change occupation (perhaps because they face lower switching costs or because they have a higher level of talent to realize). If this were indeed the case, then the wage discount of occupational followers would be delivered by a mechanism that does not imply any occupational misallocation.

We argue that such an alternative view implies a negative relationship between the father's wage and the son's likelihood of being a follower. Our theory, which is based on selection along the comparative advantage margin, implies exactly the opposite relationship: there is a higher chance that sons of high-wage (and therefore well-matched according to our theory) fathers are more likely to be followers. This is due to the fact that the sons of high–wage fathers face less of a tradeoff in their occupational choice than those of low–wage fathers.

Furthermore, the selection mechanism based on absolute advantage implies that, once we control for the individual's wage, the father's wage does not have any residual predictive power for persistence (to the extent that the individual's wage accurately captures the individual's ability level).[28] In contrast, according to our theory, the father's wage maintains its positive predictive power. To see this, notice that the probability of being a follower

[28]If we were to consider measurement error in wages, the father's wage would still retain negative predictive power.

conditional on the individual's wage is as follows:

$$\begin{aligned}P[\pi = 1|\bar{w} = 0] =& 1\\P[\pi = 1|\bar{w} = 1] =& P[\bar{w}^F = 1|\bar{w} = 1]\,\rho\\&+P[\bar{w}^F = 0|\bar{w} = 1]\,(1-\rho)\end{aligned}$$

Given that $\rho > 1/2$, this conditional probability is positively correlated with the level of the father's wage. The intuition behind this is straightforward: high–wage (i.e. well–sorted) sons are occupational followers to a larger extent if their father is also high–wage (i.e. well–sorted).

We test the opposite predictions of the two theories by regressing the likelihood of being a follower on the father's wage, both unconditional and conditional on the individual's wage (Table 22 in the Appendix). In both cases, the strongly positive correlation between the two variables is supportive of our theory, which is based on comparative advantage.

2.4 The Quantitative Model

In this section, we develop a quantitative model that extends the model in Section 2 in a number of dimensions. First, the model presented here is dynamic, such that individuals face a stochastic ageing process. Second, we have O different occupations. Third, we introduce non–pecuniary benefits (preferences) for occupations,[29] which are composed of a permanent as well as a temporary component. The permanent component is allowed to be correlated across generations, providing an additional source of occupational persistence. In constrast, the introduction of shocks to non–pecuniary benefits allows the model to generate occupational mobility over the life–cycle.[30] Finally, we introduce occupation–specific human capital. We retain the assumption that social contacts are occupation–specific, and that fathers help their sons find a job in their occupation, without internalizing that in their own occupational choice. Both social contacts and occupation–specific human capital evolve over time.

2.4.1 The Model Environment

Time is discrete ($t = 0, 1, 2, ...$) and goes on forever. The economy is divided into a discrete number of submarkets O, which represent the different occupations. A measure 2 of workers

[29]This could also be interpreted as the effect of social pressure or, more generally, any other factor that shifts the utility level for a specific occupation.

[30]This is important, in order to provide the correct mapping between the model and the data (which has an inherently dynamic nature).

populate the economy. All agents (both workers and firms) are risk–neutral and discount the future at rate λ. There are two phases of life: young and old. Every period young (old) individuals age (die) with probability ζ. All individuals who die are replaced by young unemployed workers. We assume that these shocks are perfectly correlated within a household (father–son pair). This is equivalent to assuming that individuals stop being connected to their parents when they have children, so that at each point in time only two generations are connected.[31]

Workers are indexed by i and differ along several dimensions: preferences for occupations $\boldsymbol{\phi_t^i}$, comparative advantage τ^i, occupation–specific human capital $h^i_{o,t}$ and social capital $n^i_{o,t}$ (networks). Preferences $\boldsymbol{\phi}_t^i$ are represented by a vector of size O, where the o^{th} element is the level of non–pecuniary benefits associated with occupation o. We assume that preferences have both a permanent and a transitory component, so that the period t non–pecuniary benefits are equal to the sum of the two components: $\phi^i_{o,t} = \phi^{i,P}_o + \phi^{i,T}_{o,t}$, for each o. The permanent preferences component $\boldsymbol{\phi}_t^{i,T}$, as well as the comparative advantage τ^i, are drawn at birth (i.e. on entry into the labor market) and do not change over time. In contrast, the temporary component of preferences, as well as occupation–specific human and social capital, evolve over time according to laws of motion to be specified below. Each worker is either employed or unemployed ($e^i_t \in \{0, 1\}$), and is attached to some occupation o^i.[32] Unemployed workers receive an unemployment benefit equal to b per period.

We denote the father's variables using an F superscript, so that the occupation of individual i's father will be denoted by $o^{i,F}$, the father's networks by $n_o^{i,F}$ and so on.

Upon matching, the surplus generated is split according to a linear sharing rule, such that the wage is set to a share χ of the worker's productivity.[33]

2.4.2 Search and Relocation across Occupations

We assume that search is costless and directed across occupations. Workers start their working life unemployed and decide in which occupation to look for vacancies. Employed parents help their unemployed sons find a job, by letting them use part of their occupation–specific network. As a consequence, unemployed sons find vacancies in their father's occupation with higher probability than anywhere else, *ceteris paribus*. We assume that unemployed fathers

[31] This assumption is made for simplicity and does not alter the results.

[32] Another way of modelling this would be to have the unemployed pool out of all occupations. We claim that this alternative model would yield exactly the same implications as our model, due to the CRS matching function and the fact that we focus on a symmetric equilibrium.

[33] Assuming other forms of wage determinations, such as Generalized Nash Bargaining, would be a rather extreme assumption in our setup, since in that case we would have to assume that all networks, preferences and the productivity levels in *all other* occupations are common knowledge within the match.

do not help their sons, since they are actively searching for a job themselves.

Each occupation is a separate labor market, where the number of matches between unemployed workers and vacancies is governed by the following constant returns to scale technology:

$$M_{o,t} = (U_{o,t})^{\eta}(V_{o,t})^{1-\eta}, \tag{2.33}$$

where $M_{o,t}$ denotes the total number of matches produced, $U_{o,t}$ is the total efficiency units of search exerted and $V_{o,t}$ is the measure of vacancies posted at time t in occupation o. The elasticity of the matching function with respect to $U_{o,t}$ is given by η.

Search effort is exerted both by unemployed workers and employed fathers whose sons are currently unemployed. When searching for a job, workers exploit their social networks. Networks are assumed to operate such that information on vacancies can flow within athem at zero cost and there is no competition among workers belonging to the same network. Thus, social networks can help workers find a job, and having a larger network represents an advantage for unemployed workers. This is represented in the model by an increase in the efficiency units of search that a worker can exert. In particular, it is assumed that a worker with network $n^i_{o,t}$ can exert $(1 + n^i_{o,t})$ efficiency units of search. Thus,

$$\begin{aligned} U_{o,t} = & \underbrace{\int \left(1 + n^i_{o,t}\right) \mathbb{1}\{e^i = 0; o^i = o\}di}_{\text{Units of Search of Unemployed workers}} \\ & + \underbrace{\int \xi \left(1 + n^{i,F}_{o,t}\right) \mathbb{1}\{e^i = 0; o^i = o^{i,F} = o; e^{i,F} = 1\}di}_{\text{Units of Search provided by Employed Fathers}}, \end{aligned} \tag{2.34}$$

where ξ represents the proportion of the father's network passed on to the son. The occupation–specific individual job–finding rate $p^i_{o,t}$ is the sum of the probability of an individual finding a job himself (either through his own effort or through his social network) and the probability of his father finding a vacancy for him, if they are in the same occupation:

$$p^i_{o,t} = \frac{M_{o,t}}{U_{o,t}} \left[(1 + n^i_{o,t}) + \xi(1 + n^{i,F}_{o,t})\mathbb{1}\left\{e^{i,F} = 1; o^{i,F} = o\right\}\right]. \tag{2.35}$$

Thus, at each time t workers face a single job–finding rate in their current occupation.

We assume free entry of firms, and that posting a vacancy costs κ per period. Firms in occupation o meet with a worker with probability $q_{o,t} = \frac{M_{o,t}}{V_{o,t}}$. Matches are exogenously destroyed at rate δ per period.

Workers (both employed and unemployed) can freely relocate across occupations.[34] It is assumed that when an employed worker wants to relocate, he is separated from his current match (i.e. the match is destroyed) and moves into the unemployment pool of his new occupation. Furthermore, his occupation–specific human capital and social contacts stocks fully depreciate upon changing occupation.

2.4.3 Intergenerational Transmission and Laws of Motion

We assume that upon entry into the labor market, an individual imperfectly inherits the duplet $\{\boldsymbol{\phi^P}, \tau\}$ from his father:

$$\boldsymbol{\phi^P} \sim F\left(\boldsymbol{\phi^P}|\boldsymbol{\phi^{F,P}}\right) \tag{2.36}$$

$$\tau \sim G\left(\tau|\tau^F\right) \tag{2.37}$$

The initial level of occupation–specific human and social capital is assumed to be zero in all occupations. Both human and social capital evolve over time according to the following laws of motion:

$$h_{o,t+1} = F_h\left(h_{o,t}|e_t\right) \tag{2.38}$$

$$n_{o,t+1} = F_n\left(n_{o,t}|e_t\right) \tag{2.39}$$

Finally, the temporary preference vector is drawn each period from the distribution F_ϕ:

$$\boldsymbol{\phi^T}_t \sim F_\phi \tag{2.40}$$

As already mentioned, we assume that h_o and n_o are reset to zero following a change in occupation.[35]

2.4.4 Timing

The timing of the model is as follows:

1. Old (young) workers die (age) with probability ζ. A young worker who has aged loses the connection to his father and gives birth to an unemployed son.

2. Preference shocks are realized.

3. Unemployed and employed workers decide whether or not to relocate.

[34] We abstract from direct costs of relocation, since these cannot be separately identified from the magnitude of the standard deviation of preference shocks.

[35] We do this for computational reasons, even though in principle it would be interesting to track all occupation–specific variables and have them decay over time when the worker is no longer attached to that occupation.

4. Wages and unemployment benefits are paid, and occupation–specific utility flow is realized.

5. Exogenous separations take place. Unemployed workers either find a job or remain unemployed.

6. The workers' state variables are updated according to the laws of motion.

2.4.5 The Worker's Problem

At the beginning of a worker's life, the worker's problem consists of choosing the occupation in which to search. Besides this initial choice, workers have the option of relocating into a different occupation at the beginning of each period. In what follows, we suppress the i superscript and the t subscript for readability, although all variables (except for $\boldsymbol{\phi^P}$ and τ) change over time. We denote the next period's state variables with a prime. All functional equations are conditional on the worker's state variables.

Denote the state of a worker by $\mathit{\Gamma} = \{\boldsymbol{\phi}, \tau, h_o, n_o, o, e\}$, where for simplicity o is set equal to zero for those workers who are choosing an occupation for the first time. A young worker's choices are influenced by his father who can help him find a job, so that his own state also includes his father's state $\mathit{\Gamma}^F = \{\boldsymbol{\phi^F}, \tau^F, h_o^F, n_o^F, o^F, e^F\}$. We must track all of the father's state variables because the son takes into account that: i) even if his father is unemployed today (and therefore does not affect the current job–finding rate), his father will help them him find a job in the future once he becomes employed; and ii) fathers also change occupations over the life–cycle. Conversely, we make the father's problem independent of his son's; that is, a father optimizes his choices without taking into account the impact they have on his son's problem.[36] In the following, we make explicit the dependence of a worker's value functions on his employment status and occupation. Hence, conditional on employment status and occupational affiliation, we denote the state variable of workers by $\mathit{\Omega} = \{\boldsymbol{\phi}, \tau, h_o, n_o\} \cup \mathit{\Gamma}^F$. All Bellman equations are conditional on $\mathit{\Xi}$, the aggregate state variables, even though we omit this dependance for readability. We first write the value functions for old workers (denoted by a subscript F), with the understanding that they are characterized by $\mathit{\Gamma}^F = \varnothing$.

[36]From the model's standpoint, this is akin to assuming that fathers are not altruistic (i.e., they attach zero weight to their son's value function). We make this assumption for two reasons: first, we believe that this represents more faithfully actual occupational choices (due to the timing of fertility vs. occupational choices – that is, occupational choices are typically made first); second, for simplicity, since allowing for an altruistic motive of fathers would create a complex dynamic game between fathers and sons (for instance, see Barczyk & Kredler 2014).

The Father's Problem

We denote by W^R the value of relocation across occupations:

$$W_F^R(\Omega) = \max_{j \in \{1,\ldots,O\}} \Big\{ W_{j,F}^U(\Omega) + \phi_{j,F}^T \Big\}, \tag{2.41}$$

where $\phi_{j,F}^T$ represents the temporary preference shock for occupation j. Note that unemployed workers draw a vector of size O–by–1 of preference shocks each period.

The value of unemployment in occupation o (net of the preference shock), $W_{o,F}^U$, includes the value of unemployment benefits for the current period and the expected discounted value of the future:[37]

$$W_{o,F}^U(\Omega) = b + \tilde{\lambda}\Big[p_o(\Omega)\, \mathbb{E}\left[W_{o,F}^E(\Omega')\right] + (1 - p_o(\Omega))\, \mathbb{E}\left[W_{o,F}^R(\Omega')\right] \Big]. \tag{2.42}$$

An unemployed worker is matched with a vacancy in his occupation with probability $p_o(\Omega)$, and remains unemployed with probability $(1 - p_o(\Omega))$, in which case he can decide to relocate in the next period. The future is discounted at the rate $\tilde{\lambda} = \lambda(1 - \zeta)$, in order to account for the risk of dying.

Employed workers face the relocation decision at the beginning of each period. If they decide to stay on the job, they receive the flow utility, earn the corresponding wage and stay in the same job next period, unless their match is exogenously destroyed (which happens with probability δ). Define $\hat{W}_o^E(\Omega)$ to be the value of staying employed in occupation o (that is, the value of being employed and choosing not to relocate):

$$\hat{W}_{o,F}^E(\Omega) = \phi_{o,F}^P + \phi_{o,F}^{T,E} + w(\Omega) + \tilde{\lambda}\Big[(1-\delta)\, \mathbb{E}\left[W_{o,F}^E(\Omega')\right] + \delta\, \mathbb{E}\left[W_F^R(\Omega')\right]\Big]. \tag{2.43}$$

At the start of each period, a worker's value function is as follows:

$$W_{o,F}^E(\Omega) = \max \Big\{ \hat{W}_{o,F}^E(\Omega), W_F^R(\Omega) \Big\}, \tag{2.44}$$

since this includes the possibility of leaving the job and relocating into a different occupation.

Notice that employed workers draw two sequences of preference shocks: the first determines whether or not they stay on the job, while the second determines their new occupation, in the case they wish to relocate.[38]

[37] In this case, the value function for unemployment has to be interpreted at the stage immediately *after* the relocation decision. That is, the worker has to spend the whole period unemployed in occupation o.

[38] This is done for computational convenience.

2.4.6 Wage Determination

Upon matching, wages are set by a linear sharing rule, such that the worker is paid a fixed share of his productivity. Denote $y(\tau, h)$ as the productivity level of a worker of type (τ, h). Then, the equilibrium wage is:

$$w(\tau, h) = \chi \; y(\tau, h).$$

Importantly, we assume that all payoff–relevant information is common knowledge within the match. We also assume that wages are perfectly flexible and that they are renegotiated every period, upon changes in the worker's level of human capital.

2.4.7 Relocation Across Occupations

We denote by j^* the preferred occupation in which to search, namely the occupation that maximizes the value of relocation:

$$j^*_F(\Omega) \in \operatorname{argmax}_{j\in\{1,\ldots,O\}} \Big\{ W^U_{j,F}(\Omega) + \phi^T_{j,F} \Big\}. \tag{2.45}$$

Notice that $j^*(\Omega)$ may or may not be the same or not the same as a worker's current occupation. If not, then an unemployed worker will always want to relocate, while in the case of an employed worker the choice will depend on the difference between the value functions $\hat{W}^E_{o,F}(\Omega)$ and $W^R_F(\Omega)$.

We define $R^k_{o,F}(\Omega)$ (for $k \in \{E, U\}$) as the policy function with respect to the relocation decision. Thus, when $R^k_{o,F}(\Omega) = 1$, a worker of type Ω with employment status k in occupation o optimally decides to relocate. In other words:

$$R^U_{o,F}(\Omega) = \mathbb{1}\{j^*_F(\Omega) \neq o\}.$$

$$R^E_{o,F}(\Omega) = \mathbb{1}\{W^R_F(\Omega) > \hat{W}^E_{o,F}(\Omega)\}.$$

The Son's Problem

A son faces a very similar problem to that of a father. The only difference is that he takes into account his father's decisions. As a result, a young worker can decide to relocate as a consequence of a change in his own state variables (preferences) or because his father's state variables have changed, in which case he might want to follow his father in order to benefit from a higher probability of finding a job.

The expression for the value of relocation remains identical:

$$W_S^R(\Omega) = \max_{j\in\{1,\ldots,O\}} \Big\{ W_{j,S}^U(\Omega) + \phi_{j,S}^T \Big\}. \tag{2.46}$$

The value of unemployment and employment are augmented by the fact that the worker will become a father in the next period with probability ζ:

$$\begin{aligned} W_{o,S}^U(\Omega) = b + \lambda\Big[& p_o(\Omega)\ \left(\zeta\,\mathbb{E}\left[W_{o,F}^E(\Omega')\right] + (1-\zeta)\mathbb{E}\left[W_{o,S}^E(\Omega')\right]\right) \\ & +(1-p_o(\Omega))\ \left(\zeta\,\mathbb{E}\left[W_{o,F}^R(\Omega')\right] + (1-\zeta)\mathbb{E}\left[W_{o,S}^R(\Omega')\right]\right)\Big]. \end{aligned} \tag{2.47}$$

$$\begin{aligned} W_{o,S}^E(\Omega) = \max\Big\{ & \phi_{o,S}^P + \phi_{o,S}^{T,E} + w(\Omega) \\ & +\lambda\Big[(1-\delta)\ \left(\zeta\,\mathbb{E}\left[W_{o,F}^E(\Omega')\right] + (1-\zeta)\mathbb{E}\left[W_{o,S}^E(\Omega')\right]\right) \\ & +\delta\ \left(\zeta\,\mathbb{E}\left[W_F^R(\Omega')\right] + (1-\zeta)\mathbb{E}\left[W_S^R(\Omega')\right]\right)\Big], W_S^R(\Omega)\Big\}. \end{aligned} \tag{2.48}$$

The relocation decisions $R_{o,S}^U(\Omega)$ and $R_{o,S}^E(\Omega)$ are isomorphic to those of the father, and are defined according to the above–specified value functions.

2.4.8 The Firm's Problem

A firm is represented by a single job that is either filled or vacant. The value function for a job filled with a worker of type Ω is denoted by $J_{o,k}(\Omega)$, where $k \in \{F, S\}$ denotes the age of the worker. Provided that the worker does not choose to leave the firm, this value function includes the current profit (given by production net of the wage payment) and the continuation value of keeping the worker. The value of keeping an old worker is given by:

$$\begin{aligned} J_{o,F}(\Omega) = {} & \mathbb{1}\{R_{o,F}^E(\Omega) = 0\}\Big[y(\tau, h_o) - w(\Omega) + \tilde{\lambda}\big[(1-\delta)\mathbb{E}\left[J_{o,F}(\Omega')\right] + \delta V_o'\big]\Big] \\ & +\mathbb{1}\{R_{o,F}^E(\Omega) = 1\}\, V_o. \end{aligned} \tag{2.49}$$

The output of the match is given by the function $y(\tau, h_o)$, which we assume to be increasing in both arguments. The match is exogenously destroyed with probability δ in the next period (in which case, as in the case of endogenous separation, the firm is left with the value of a vacancy V_o). With probability $(1-\delta)$, the match continues, and the state variables of the worker are updated.

The value of keeping a young worker is as follows:

$$J_{o,S}(\Omega) = \mathbb{1}\{R^E_{o,S}(\Omega) = 0\}\Big[y(\tau, h_o) - w(\Omega) + \lambda\big[(1-\delta)\big(\zeta\,\mathbb{E}\left[J_{o,F}(\Omega')\right] + (1-\zeta)\mathbb{E}\left[J_{o,S}(\Omega')\right]\big) + \delta V'_o\big]\Big] + \mathbb{1}\{R^E_{o,S}(\Omega) = 1\}\, V_o. \tag{2.50}$$

This equation has the same interpretation as the one for an old worker, except that it allows for the possibility of a worker becoming old (as a result of the ζ shock) and the match continuing.

The value of a vacancy V_o is given by the expected profits less the posting cost κ.

$$V_o = -\kappa + q_o\,\mathbb{E}\left[J_o(\Omega')\right] + (1-q_o)V'_o, \tag{2.51}$$

where the expectation is taken over the distribution of unemployed workers in occupation o, which include all possible types Ω and possible ages $\{F, S\}$.

2.4.9 Equilibrium Definition

We focus on a symmetric steady state equilibrium (SS) in which all value functions and relocation decisions are constant over time. As a result, worker flows are also constant over time (the equations describing such flows are relegated to the Appendix).

Definition: An SS equilibrium is a set of value functions $W^U_{o,F}(\Omega)$, $W^U_{o,S}(\Omega)$, $W^E_{o,F}(\Omega)$, $W^E_{o,S}(\Omega)$, V_o; relocation decisions $R^U_{o,F}(\Omega)$, $R^U_{o,S}(\Omega)$, $R^E_{o,F}(\Omega)$, $R^E_{o,S}(\Omega)$, $j^*_F(\Omega)$, $j^*_S(\Omega)$; labor market tightness θ_o; wages $w_o(\Omega)$; laws of motion for the individual state variables; and laws of motion of unemployed and employed workers over all occupations, such that:

- The value functions for workers and relocation decisions satisfy Equations (2.42), (2.44), (2.47), (2.48).
- There is free entry into all occupations: $V_o = 0\ \forall o \in \{1, .., O\}$.
- Labor market tightness satisfies Equation (2.51).
- Wages satisfy Equation (2.31).
- Individual state variables evolve according to Equations (2.38), (2.39) and (2.40).
- Distributions of workers evolve according to Equations (41), (42), (43) and (44) (in the Appendix).

- The measures of employed and unemployed workers of each type Ω are constant over time.
- Flows of employed and unemployed workers of each type Ω are constant over time.

2.5 Quantitative Analysis

In this section, we quantitatively assess the importance of each of the channels operating in the model (ability, preferences and networks transmission) in delivering occupational persistence. We first assign values to the structural parameters of our model, and then use the calibrated model to decompose occupational persistence and perform welfare analysis and policy experiments.

2.5.1 Calibration Strategy

Our strategy involves exogenously fixing some of the parameters, and jointly calibrating all the rest to relevant moments of the UK data. First, we fix the number of occupations O to 9 in order to be consistent with the SOC–1 digit aggregation. One period in the model corresponds to one month, and therefore the discount factor λ is set to 0.9966. The age shock ζ is set so as to deliver an average working life of 40 years (20 as a young worker and 20 as an old one), implying a value of 0.00416. We also fix the surplus sharing rule parameter χ to 0.7 and the scale of the matching function A to 0.1. Finally, we fix $\eta = 0.5$ following Petrongolo and Pissarides (2001).

We calibrate the rest of the parameters in order to match relevant features of the data. In order to do so, we first need to choose the grid of possible values of the worker–specific state variables, as well as the functional forms describing their laws of motion. We let h and n take two different values, with the lower one being normalized to 1:

$$h \in \{1, 1 + \hat{h}\},$$

$$n \in \{1, 1 + \hat{n}\},$$

where $\hat{h}$ and $\hat{n}$ represent the premia of human capital and networks that are associated with tenure. The accumulation/depreciation of these occupation–specific variables is subject to a Markov-process characterized by the following parameters: p_h^+, p_h^-, p_n^+, p_n^-, where the $+$ and $-$ superscripts denote accumulation (when employed) and depreciation (when unemployed) probabilities, respectively.

We also assume that each worker has a talent τ in one occupation, in which he has a productivity premium $\hat{\tau}$. The minimum level of productivity is normalized to 1. The match production function $y(\tau, h_o)$ is assumed to be:

$$y(\tau, h_o) = \begin{cases} h_o & \text{if} \quad o \neq \tau \\ \hat{\tau}\, h_o & \text{if} \quad o = \tau \end{cases}$$

In the same way, we assume that each worker has a preferred occupation ϕ, where he obtains a non–pecuniary benefit ($\hat{\phi}$) that is higher than elsewhere. At the same time, we also normalize the baseline level of preferences for a job $\bar{\phi}$ to 0. Both τ and ϕ are drawn at birth, with ρ_τ and ρ_ϕ being the probabilities of drawing the same values as the father ($\rho = 1$ represents perfect persistence). Let τ and ϕ be respectively the occupations in which a worker has a comparative advantage and the preference premium:

$$\tau = \begin{cases} \tau^F & \text{w.p.} \quad \rho_\tau \\ o \neq \tau^F & \text{w.p.} \quad \frac{(1-\rho_\tau)}{O} \quad \forall\, o \neq \tau^F \end{cases}$$

$$\phi = \begin{cases} \phi^F & \text{w.p.} \quad \rho_\phi \\ o \neq \phi^F & \text{w.p.} \quad \frac{(1-\rho_\phi)}{O} \quad \forall\, o \neq \phi^F \end{cases}$$

Finally, we assume that the idiosyncratic preference shocks are drawn from a Type–1 Extreme distribution, with standard deviation σ.[39]

Together with κ and ξ, we have a total of 14 parameters to be calibrated. We search for the parameter configuration that minimizes the following loss function:

$$\mathcal{L} = \frac{\sqrt{\sum_{n=1}^{K} \left(\frac{M_n(\Theta) - T_n}{T_n}\right)^2}}{K},$$

where T is a K–by–1 vector containing our target statistics and M is a K–by–1 vector containing the statistics generated by the model (we choose $K = 14$, so that the model is exactly identified). Table 2.6 contains the list of all parameters of the model, each of which is associated with the identifying moment in Column 4.

The vacancy posting cost κ is calibrated in order to match the average monthly UE rate, which is 0.1251. A lower posting cost induces more entry from the firms' side, implying higher tightness and higher finding rates. The exogenous separation rate δ is set in order to match the average EU rate, which is 0.0047. The transmission of networks ξ is set to replicate the

[39] This is a standard assumption in the literature on occupational choice. See for instance Wiczer (2014).

job–finding rate premium (of 0.0546) of occupational followers w.r.t. movers. A higher value of ξ implies that a son can take advantage of a larger proportion of his father's network. The transmission of comparative advantage is calibrated to match the differential in the likelihood of occupational persistence by the father's wage. In particular, we target the 2.3% difference in the probability of being an occupational follower if the father's wage is above the average, as observed in the BHPS data. An increase in ρ_τ increases the chances that the occupation of the father is also that in which the son finds his comparative advantage *when the father is well–matched*, thus increasing persistence for those with a high–wage father. The parameter governing the transmission of preferences ρ_ϕ is pinned down by asking the model to replicate the occupational persistence observed in the data (likelihood ratio of 1.72 at the 1–digit level). In other words, we are using the transmission of preferences as the residual channel to entirely match occupational persistence, above and beyond the persistence already generated by the other two channels.

Next, the comparative advantage premium $\hat{\tau}$ is calibrated to match the level of within–occupation log wage variance. The rationale for this is that the more heterogeneous are the potential productivity levels of workers across occupations, the more dispersed equilibrium wages will be. The networks premium $\hat{n}$ is calibrated to match the proportion of jobs found through networks in the UK, which is 0.23 (Pellizzari 2010b). The higher $\hat{n}$ is, the more networks will be present in the economy and used for job search. The preference premium $\hat{\phi}$ is chosen to replicate the average wage discount (of 0.0763 log points) of occupational followers. High values of $\hat{\phi}$ imply that preferences are relatively more important than comparative advantages in occupational choice. The standard deviation of the preference shocks distribution (σ) is calibrated to the probability of switching occupation after an unemployment spell (0.3567). The larger the variance of the shocks, the more frequently occupational changes occur. The value of unemployment b is calibrated to match the average replacement rate in the UK of 0.53 (OECD).

Moreover, we calibrate $p_h^+ = 0.0166$ which, together with $\hat{h} = 0.26$, implies that the average occupational returns after 5 years are equal to 26%, as observed in the data. The probability of losing human capital p_h^- is calibrated to match the average wage discount after unemployment of 7.6% (Arulampalam 2001). The probability of losing networks p_n^- is set to match the slope of the JF rate–unemployment duration profile. In particular, we ask the model to replicate the drop in finding rates that occur between the first and second months of unemployment duration. Finally, we calibrate the probability of accumulating networks p_n^+ to the conditional correlation of job–finding rates with months of past occupational tenure, which is 0.008.

2.5.2 Calibration Results

The model is able to precisely match all targets, both the cross–sectional and the inter–generational ones. We are able to replicate the full extent of occupational persistence observed in the data by making both preferences and comparative advantages persistent across generations (where the probability of inheriting them is 0.147 and 0.141, respectively).The proportion of parental networks exploited by the son is 0.325, which generates the same job–finding rate premium as in the data.

A large degree of heterogeneity is needed in order to match the data moments: the preference premium is 0.811, while the comparative advantage premium is even higher, at 1.008. The networks premium is also substantial (1.104), whereas the human capital premium is 0.26 (taken directly from the data). The accumulation of both human capital and networks is slow: the monthly probability of human capital growing is 0.0166, while for networks it is 0.005. In contrast, their depreciation during unemployment is substantially faster: the monthly probability of networks depreciating is 0.115, while for human capital it is 0.79.

We calculate that in this economy posting a vacancy costs around 4 times the average wage. Finally, the exogenous match destruction rate is 0.003, with the rest of the EU flows being accounted for by endogenous separations.

Parameter	Description	Value	Target/Source	Data	Model
Intergenerational Transmission					
ξ	Transmission of Networks	0.325	JF premium of followers (BHPS)	0.055	0.055
ρ_τ	Transmission of Comparative Advantage	0.141	Difference in Proportion of Followers by Father's wage (BHPS)	0.023	0.023
ρ_ϕ	Transmission of Preferences	0.147	Interg. Occupational Persistence (Lik. Ratio, BHPS)	1.720	1.720
Heterogeneity and Laws of Motions					
$\hat{h}$	HC premium	0.260	Average occupational tenure returns after 5 years (BHPS)	-	-
$\hat{n}$	Networks premium	1.104	Proportion of jobs found through contacts (Pellizzari 2010b)	0.230	0.230
$\hat{\tau}$	Comparative Advantage premium	1.008	Within–occupation log wage variance (BHPS)	0.166	0.166
$\bar{\phi}$	Baseline preference for jobs	0	Normalization	-	-
$\hat{\phi}$	Preference premium	0.811	Wage discount of followers (BHPS)	0.076	0.076
p_h^+	Probability of accumulating HC (employed)	0.0166	Average occupational tenure returns after 5 years (BHPS)	0.260	0.260
p_h^-	Probability of losing HC (unemployed)	0.790	Average wage discount after unemp. (Arulampalam 2001)	0.076	0.076
p_n^+	Probability of accumulating networks (employed)	0.005	Regression of JF rate vs. past occupational tenure (BHPS)	0.008	0.008
p_n^-	Probability of losing networks (unemployed)	0.115	JF rate–unemployment duration profile (see text, BHPS)	1.066	1.066
σ	Standard deviation of preference shocks	0.254	Occupational change rate, after U spell (monthly, BHPS)	0.357	0.357
Environment					
O	Number of occupations	9	1-digit SOC aggregation	-	-
κ	Vacancy posting cost	5.269	Average UE rate (monthly, BHPS)	0.125	0.125
δ	Exogenous separation rate	0.003	Average EU rate (monthly, BHPS)	0.005	0.005
λ	Discount factor	0.9966	From literature	-	-
ζ	Age shock	0.00416	Average length of worklife: 20 (young) + 20 (old) years	40	40
b	Unemployment benefit	0.745	Average replacement rate (OECD)	0.530	0.530
χ	Surplus sharing rule	0.7	Normalization	-	-
A	TFP parameter of matching function	0.1	Normalization	-	-
γ	Elasticity of matching function w.r.t. unemp.	0.5	Petrongolo and Pissarides (2001)	-	-

Table 2.6. Calibration Results

2.5.3 Occupational Persistence Decomposition and Welfare Analysis

The model allows us to study the factors behind occupational choice, and how they differ in importance between followers and movers. In Table 2.7, we calculate how often the occupational choice is aligned with each of the three possible factors (parental networks, comparative advantage, and preferences) under the baseline calibration.

	All	Followers	Movers
Sorting along comparative advantage (fathers)	0.656	-	-
Sorting along preferences (fathers)	0.455	-	-
Sorting along parental networks (sons)	0.183	0.959	0.000
Sorting along comparative advantage (sons)	0.708	0.624	0.729
Sorting along preferences (sons)	0.402	0.461	0.388
Average log wage (sons)	0.292	0.232	0.307
Average unemployment rate (sons)	0.061	0.045	0.065

Table 2.7. Occupational sorting.

For fathers, comparative advantage seems to be more important than preferences for occupational sorting: 66% (46%) of fathers choose the occupation in which they have a comparative advantage (preference). Among sons, the same holds true: about 71% of them pick the occupation in which they are most productive, whereas about 40% of them pick their preferred occupation. Finally, the occupational choice is aligned with parental networks in 18% of the cases. Striking differences in sorting arise between followers and movers: the former put more weight on preferences in their occupational decision (46% versus 39% of movers) and less on comparative advantage (62% versus 73% of movers). As a consequence, followers earn lower wages, as can be seen in row 6 of Table 2.7. At the same time, followers have better employment prospects than movers, with an average unemployment rate of 4.5%, versus 6.5% for movers. Summing up, the model economy generates a clear sorting of workers in the two regions of high–employment/low–wages and low–employment/high–wages.

However suggestive, these correlations are not yet informative about the nature of occupational persistence. For this reason, we now sequentially shut down each of the three channels delivering occupational persistence. In this way, we are able to: i) quantify the contribution of each channel to overall persistence; and ii) evaluate welfare in each different scenario. Table 2.8 shows the results of the experiments: column 1 is the case of the baseline economy, while in columns 2-8 we set $\xi = 0$, $\rho_\tau = 1/O$ and $\rho_\phi = 1/O$, along with all possible combinations of these parameter changes.

First, all factors seem to matter for occupational persistence, though by differing degrees. Shutting down parental networks generates the largest drop in persistence, of about 79% (column 2), while comparative advantage and preferences transmission (columns 3 and 4) respectively account for about 19% and 10% of persistence. Moreover, networks transmission appears to work in conjunction with the other sources of persistence, since shutting down these channels in pairs delivers less of a drop than the sum of the effects separately (columns 5 and 6 vs 2–4). In contrast, comparative advantage and preferences work independently from one another (the drop in column 7 is equal to or even larger than the combined effects of column 3 and 4). To better understand the surprisingly large effect of networks and how they interact with the other factors, in Figure 2.4 we plot the average policy function (occupational choice) of unemployed workers whose father is employed and whose comparative advantage and preferences are not aligned.[40]

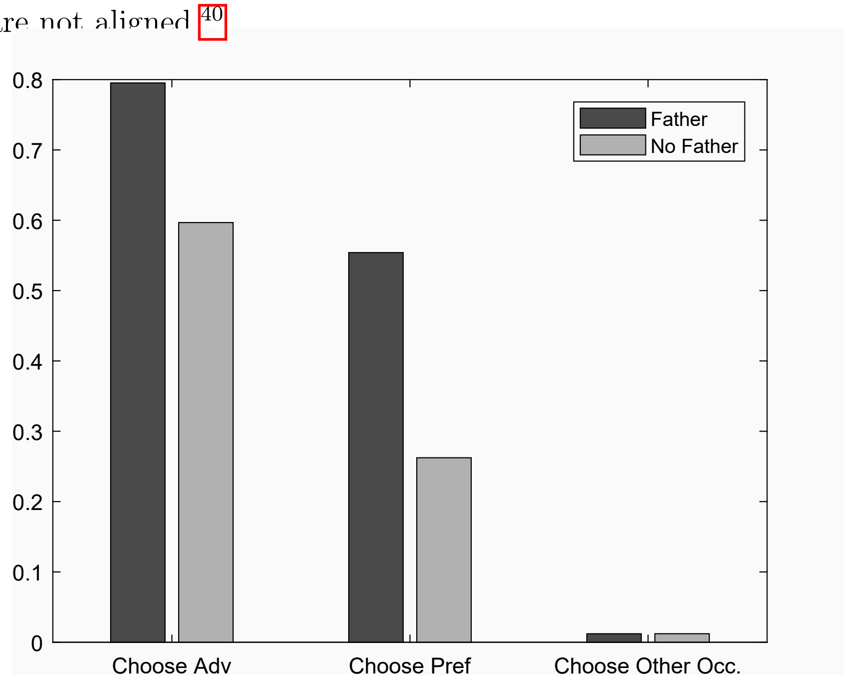

Figure 2.4. Plot of Average Policy Function (Occupational Choice) for unemployed workers with comparative advantage and preference in different occupations.

As already noted, individuals in this economy tend to choose their occupation more according to comparative advantage than preferences. Moreover, the presence of an employed father strongly impacts the occupational choice of his son. For instance, on average, individuals choose the occupation in which they have a comparative advantage with a probability of 80% if the father is also employed in that occupation. This probability drops to 60% if

[40]The workers for which comparative advantage and preferences are not aligned represent the large majority of the population. In the Appendix, we show the same average policy function of those workers for whom the two factors are aligned.

the father is employed in a different occupation (compare the first two bars in Figure 2.4). This effect is even larger for preferences: the occupation for which preference and parental networks are aligned is chosen in 55% of the cases, while the preferred occupation without parental networks is chosen in only 26% of the cases. It is significant that the benefits from the father's networks alone are not enough to attract the son. Indeed, by comparing the last two bars, one can easily see that choosing an occupation with neither comparative advantage nor preferences is almost never an attractive option, with or without the father's network. The reason for this stark difference is that the value of employment differs from the value of unemployment to a larger extent in occupations with either comparative advantage or preference than in other occupations. By improving the chances of employment, parental networks act as a multiplier of these differentials, therefore playing a much larger role in conjunction with these other fixed factors than alone.

Second, the welfare consequences of a reduction in persistence vary widely across the experiments. When we shut down parental networks (column 2), welfare improves by 0.11%, due to the improved allocation of workers to occupations (sorting along the productivity dimension increases from 71% to 74%) and despite a worsened sorting along the preferences dimension (which drops from 40% to 37%). As a consequence of the increase in the productivity of the workforce, output per worker increases and wage variance decreases. Also, unemployment improves (declines by 1.5%) despite the fact that less efficiency units of search are now exerted in the market, since firms react to the change in average labor productivity by posting more vacancies. In contrast, when we shut down the transmission of comparative advantage (column 2), welfare decreases by 0.04%, while output per worker declines (sorting along the productivity dimension worsens, while sorting along the preferences dimension improves) and unemployment rises (by 0.33%). Finally, shutting down preferences transmission (column 3) has a similar though smaller effect to that of shutting down parental networks. Thus, productivity becomes more dominant in an individual's choice, output per worker increases and unemployment decreases. The net effect of these changes, despite a worsened sorting along the preferences dimension, is an increase in welfare of 0.03%.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No parental net.	$(\xi = 0)$	-	✓	-	-	✓	✓	-	✓
No comp. adv. trans.	$(\rho_\tau = 1/O)$	-	-	✓	-	✓	-	✓	✓
No pref. trans.	$(\rho_\phi = 1/O)$	-	-	-	✓	-	✓	✓	✓
Occupational Persistence		1.720	1.154	1.582	1.649	1.035	1.119	1.508	1.000
(Δ% from baseline)		0.000	(-78.60)	(-19.23)	(-9.84)	(-95.10)	(-83.50)	(-29.37)	(-100.00)
Welfare (Δ% from baseline)		0.000	(0.112)	(-0.044)	(0.034)	(0.112)	(0.112)	(-0.010)	(0.112)
Sorting along comparative advantage (sons)		0.708	0.737	0.704	0.714	0.737	0.737	0.709	0.737
Sorting along preferences (sons)		0.402	0.373	0.407	0.397	0.373	0.374	0.401	0.373
Sorting along comparative advantage (fathers)		0.656	0.674	0.653	0.660	0.674	0.674	0.657	0.674
Sorting along preferences (fathers)		0.455	0.436	0.458	0.451	0.437	0.437	0.454	0.437
Output per worker (=1 in baseline)		1.000	1.017	0.997	1.003	1.017	1.017	1.001	1.017
Log Wage Variance (Δ% from baseline)		0.166	(-4.230)	(0.640)	(-0.789)	(-4.230)	(-4.230)	(-0.137)	(-4.230)
Welfare CV (Δ% from baseline)		0.147	(-0.111)	(0.022)	(-0.035)	(-0.111)	(-0.111)	(-0.0126)	(-0.111)
Unemployment Rate (Δ% from baseline)		0.061	(-1.505)	(0.334)	(-0.296)	(-1.506)	(-1.506)	(0.035)	(-1.506)
Average UE Rate (Δ% from baseline)		0.125	(1.728)	(-0.289)	(0.314)	(1.728)	(1.728)	(0.028)	(1.728)
Average EU Rate (Δ% from baseline)		0.005	(-0.117)	(0.052)	(0.030)	(-0.118)	(-0.118)	(0.083)	(-0.118)
Equilibrium Tightness		1.565	(3.486)	(-0.577)	(0.628)	(3.486)	(3.486)	(0.057)	(3.486)

Table 2.8. Occupational Persistence Decomposition and Welfare Analysis.

2.5.4 Other Counterfactual Experiments

2.5.4.1 The Importance of Multiple Transmission Channels

The model is characterized by several degreess of heterogeneity, and intergenerational persistence is influenced by three different factors (comparative advantage, preferences, networks). One interesting exercise we will now carry out is to shut down some of these channels and recalibrate the model in order to match the data with fewer degrees of freedom. This allows us to understand whether all model dimensions are really necessary in order to replicate the data patterns. We keep the transmission of productive abilities as the only transmission channel, since it embeds in a reduced–form way genetic transmission, educational choices and human capital transfers in general, which are the channels most commonly emphasized in the intergenerational literature. Therefore, we set $\xi = 0$ and $\rho_\phi = 1/O$ and ask the model to match all data moments in Table 2.6 except for the JF rate premium and the wage discount. The rationale for our choice is that, with only one source of persistence, the model cannot replicate either of these two moments.

In general, the fit of the model is now substantially worse.[41] The model is not able to fully account for occupational persistence, producing a likelihood ratio of only 1.597. The value of ρ_τ is set as high as possible, since this is now the only source of occupational persistence. By doing so, the model largely overshoots the differentials in the propensity to be a follower by the father's wage (in fact, it is more than 10 times larger than in the data). Another consequence is that, in order to generate high persistence, the model completely fails to generate the wage discount (non–targeted) of followers relative to movers (and actually generates a wage premium). This reflects the fact that productivity transmission is the only channel producing persistence, and therefore occupational followers base their occupational choice on productivity to a larger extent than movers. By construction, the model also cannot replicate the job–finding rate premium of followers (non–targeted), since networks transmission is shut down.

When we shut down occupational persistence in the restricted economy (Table 2.9), it turns out that persistence is absolutely neutral in this economy. Shutting down the only source of persistence delivers an identical economy in all dimensions, except for occupational persistence, which vanishes completely. This is because in this economy persistence is not a sign of distortions in the occupational choice of individuals. Furthermore, persistence in this economy is generated only by the fact that father–son pairs tend to be more similar than two randomly picked workers. In this sense, occupational persistence is no longer a reflection

[41] The calibration table of the restricted model can be found in Appendix 3.7.

of the fact that sons *care* about the occupational choices of their father and are affected by them. In other words, a son's policy and value functions are now independent of his father's state variables.

		(1)	(2)
No parental net.	$(\xi = 0)$	n.a.	n.a.
No comp. adv. trans.	$(\rho_\tau = 1/O)$	-	✓
No pref. trans.	$(\rho_\phi = 1/O)$	n.a.	n.a.
Occupational Persistence		1.597	1.000
(Δ% from baseline)		-	(-100.00)
Welfare (Δ% from baseline)		-	(0.000)
Sorting along comparative advantage (sons)		0.344	0.344
Sorting along preferences (sons)		0.767	0.767
Sorting along comparative advantage (fathers)		0.365	0.365
Sorting along preferences (fathers)		0.746	0.746
Output per worker (=1 in baseline)		1.000	1.000
Log Wage Variance (Δ% from baseline)		0.181	(0.000)
Welfare CV (Δ% from baseline)		0.153	(-0.000)
Unemployment Rate (Δ% from baseline)		0.067	(-0.000)
Average UE Rate (Δ% from baseline)		0.112	(0.000)
Average EU Rate (Δ% from baseline)		0.004	(-0.000)
Equilibrium Tightness		1.255	(0.000)

Table 2.9. Occupational Persistence Decomposition and Welfare Analysis (Restricted Model).

2.5.4.2 The Role of Search Frictions

Search frictions are an important determinant of productive mismatch in our framework. Therefore, it is interesting to investigate the extent to which the severity of frictions affects the importance of parental networks, the level of persistence and the overall allocation. To do so, we impose the degree of frictions implied by the monthly finding rates of different economies on the UK baseline calibration. We focus on two polar cases among OECD countries: the US and Spain. We target the average monthly job–finding rates estimated in Hobijn & Şahin (2009): 0.5630 for the US and 0.0389 for Spain. We recalibrate κ in order to match these rates, keeping all other parameters constant; the implied new values of the parameter are 1.30 (for the US) and 15 (for Spain). We repeat the persistence decomposition exercises of subsection 2.5.3 for both of the counterfactual economies, with the results shown in Table 2.10.

Two main results stand out: First, the importance of parental networks crucially depends on the size of the frictions. In the low–friction economy, removing parental networks barely affects persistence (which is reduced by only 2.3%), whereas the reduction in the high–friction economy is much more pronounced (79%). At the same time, the removal of networks is welfare–improving in the high–friction economy (since it raises average labor productivity), but is welfare–decreasing in the low–friction economy (since it crowds out occupational choice along the preferences dimension, due to the fact that networks are basically not generating any occupational choice that is not based on productivity in the baseline equilibrium). Relatedly, we find that occupational persistence is much higher in the high–friction economy than in the low–friction economy, other things being equal (likelihood ratio of 1.68 vs. 1.25).

Second, by comparing column 1 to column 5, we can see that search frictions may be responsible for high unemployment and low productivity at the same time. This is a reflection of the fact that networks are more distortionary in environments with large frictions, where individuals are more willing to trade their productive advantage for better employment prospects.

		($\kappa = 1.34$)				($\kappa = 15.00$)			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No parental net.	($\xi = 0$)	-	✓	-	-	-	✓	-	-
No comp. adv. trans.	($\rho_\tau = 1/O$)	-	-	✓	-	-	-	✓	-
No pref. trans.	($\rho_\phi = 1/O$)	-	-	-	✓	-	-	-	✓
Occupational Persistence		1.254	1.248	1.005	1.254	1.683	1.143	1.579	1.586
(Δ% from baseline)		-	(-2.285)	(-98.112)	(-0.003)	-	(-79.136)	(-15.180)	(-14.250)
Welfare (Δ% from baseline)		-	(-0.324)	(-0.066)	(-0.000)	-	(0.094)	(-0.052)	(0.044)
Sorting along comparative advantage (sons)		0.999	0.999	0.999	0.999	0.604	0.612	0.599	0.609
Sorting along preferences (sons)		0.112	0.112	0.112	0.112	0.508	0.499	0.512	0.502
Sorting along comparative advantage (fathers)		0.924	0.924	0.924	0.924	0.584	0.588	0.581	0.587
Sorting along preferences (fathers)		0.187	0.187	0.187	0.187	0.528	0.524	0.531	0.525
Output per worker (Δ% from baseline)		2.364	(0.000)	(-0.001)	(0.000)	1.888	(0.549)	(-0.286)	(0.345)
Unemployment Rate (Δ% from baseline)		0.011	(1.866)	(0.307)	(0.001)	0.183	(-0.709)	(0.311)	(-0.279)

Table 2.10. Occupational Persistence Decomposition and Welfare Analysis. Numbers in parentheses are relative changes from baseline. Counterfactual Experiments: Columns (1)-(4) are under the baseline calibration and the US level of labor market frictions; Columns (5)-(8) are under the baseline calibration and Spanish level of labor market frictions.

2.5.4.3 Policy Experiment: Unemployment Benefits

We now look at how changes in unemployment benefits affect the equilibrium of the economy. In order to assess the welfare consequences of such changes, we introduce a lump–sum tax τ on existing matches (which is split between workers and firms, where χ is the share paid by the workers) and a government budget constraint. The new value functions for employed workers and firms are as follows:

$$\begin{aligned} W_o^E(\Omega) = \max\Big\{ & \phi_o^P + \phi_o^{T,E} + w(\Omega) - \chi\tau + \\ & \tilde{\lambda}\Big[(1-\delta)\,\mathbb{E}\left[W_o^E(\Omega')\right] + \delta\,\mathbb{E}\left[W^R(\Omega')\right]\Big], W^R(\Omega)\Big\}. \end{aligned} \tag{2.52}$$

$$\begin{aligned} J_o(\Omega) = {} & \mathbb{1}\{R_o^E(\Omega)=0\}\Big[y(\tau,h_o) - w(\Omega) - (1-\chi)\tau + \tilde{\lambda}\big[(1-\delta)\mathbb{E}\left[J_o(\Omega')\right] + \delta V_o'\big]\Big] \\ & + \mathbb{1}\{R_o^E(\Omega)=1\}\, V_o. \end{aligned} \tag{2.53}$$

The government balances its budget in each period. That is, the change in unemployment benefits from the baseline equilibrium must be financed by the tax revenues:

$$\Delta b\, u = \tau(1-u), \tag{2.54}$$

where u is the unemployment rate of the economy. The rest of the model remains unchanged.

Some of the channels commonly emphasized in the literature through which unemployment benefits have an effect on the economy, such as the scope for redistribution (in the presence of risk aversion) or the disincentivizing effect on the search efficiency units choice, are absent in our framework. At the same time, unemployment benefits interact very strongly with the main tradeoff at work in our model. Thus, an increase (decrease) in the value of unemployment benefits decreases (increases) the distance between the value of employment and unemployment for workers. As a consequence, parental networks become less (more) important in the son's choice, since insurance against unemployment becomes less (more) valuable. This implies that workers sort more (less) according to productivity and preferences. To the extent that this increase in sorting is more prominent along the comparative advantage dimension, unemployment benefits can produce productivity gains.[42]

In the quantitative experiment (Table 2.11), an increase of 10% (25%) in b favours sorting along the preferences dimension, whereas it slightly dampens the sorting along the comparative advantage dimension. As a consequence, output per worker decreases by about

[42] This mechanism has a very similar flavor to that in Acemoglu & Shimer (2000) and Golosov *et al.* (2013).

0.1% (0.3%). At the same time, occupational persistence decreases (since parental networks are less attractive) and unemployment increases (since unemployment is now a more attractive option). The overall net effect on welfare is negative (-0.09% and -0.31%), reflecting the fact that the tax rate increases proportionally more than b, given that unemployment increases. Columns 4 and 5 show that decrease in b have qualitatively opposite effects.

When we repeat the same exercises under the restricted calibration (lower part of Table 2.11), we find the effect to be similar. One important difference is that, under the restricted calibration, increases in b do indeed lead to improvements in output per worker, even if the magnitude of the change is quite small (0.2% and 0.4%). The increase in unemployment is therefore smaller than in the baseline case, reflecting a relatively higher level of firm entry (in response to the increase in labor productivity). Interestingly, welfare moves in the same direction in both model specifications, even though the magnitude of the change is very different. For instance, an increase of 25% in b generates a welfare loss of 0.31% under the baseline calibration, while in the restricted calibration the loss is only 0.16% . Hence, it turns out that allowing for multiple sources of persistence is also relevant for the assessment of labor market policy in general.

2.6 Conclusions

We investigated the determinants of occupational persistence across generations. When persistence is generated from multiple sources, it is crucial to assess their relative importance in order to understand the relationship between persistence and misallocation, and to derive welfare implications. A simple model of occupational persistence and search frictions, in which both abilities and contacts are transmitted across generations, delivers clear–cut testable predictions on employment prospects and wages, which are confirmed in UK data.

We extended the theory to a more complete dynamic model of occupational choice, allowing for mobility over the life–cycle and accumulation/depreciation of human and social capital. We found that parental networks account for the bulk of occupational persistence and that a model based only on transmission of ability (the restricted model) would be at odds with several features of the data. A key result of our quantitative analysis is that only occupational persistence generated by parental networks and preferences transmission may be detrimental to welfare. Furthermore, we show that search frictions interact with parental networks, amplifying their importance and their adverse effects on the aggregate equilibrium.

We evaluate the cost of increasing unemployment benefits and find that the restricted model understates the cost by a factor of two. Hence, we conclude that modeling multiple

Change in b (Δ% from baseline)	(1) -	(2) +10%	(3) +25%	(4) -10%	(5) -25%
Baseline Economy					
Occupational Persistence	1.720	1.702	1.673	1.737	1.762
(Δ% from baseline)	-	(-2.516)	(-6.500)	(2.418)	(5.875)
Welfare (Δ% from baseline)	-	(-0.091)	(-0.311)	(0.058)	(0.094)
Sorting along comparative advantage (sons)	0.708	0.707	0.704	0.709	0.710
Sorting along preferences (sons)	0.402	0.404	0.407	0.402	0.401
Sorting along comparative advantage (fathers)	0.656	0.655	0.652	0.657	0.658
Sorting along preferences (fathers)	0.455	0.456	0.459	0.454	0.454
Output per worker (=1 in baseline)	1.000	0.999	0.997	1.001	1.001
Unemployment Rate (Δ% from baseline)	0.061	(3.694)	(11.369)	(-2.884)	(-6.061)
Restricted Model					
Occupational Persistence	1.597	1.607	1.623	1.589	1.578
(Δ% from baseline)	-	(1.545)	(4.224)	(-1.380)	(-3.185)
Welfare (Δ% from baseline)	-	(-0.054)	(-0.164)	(0.040)	(0.080)
Sorting along comparative advantage (sons)	0.344	0.346	0.350	0.342	0.340
Sorting along preferences (sons)	0.767	0.765	0.761	0.769	0.771
Sorting along comparative advantage (fathers)	0.365	0.367	0.370	0.363	0.361
Sorting along preferences (fathers)	0.746	0.744	0.741	0.748	0.750
Output per worker (=1 in baseline)	1.000	1.002	1.004	0.999	0.997
Unemployment Rate (Δ% from baseline)	0.067	(2.476)	(6.925)	(-2.156)	(-4.890)

Table 2.11. Policy Experiment: effect of changes in unemployment benefits.

sources of intergenerational transmission is crucial not only to understanding the consequences of persistence, but also for the assessment of labor market policy.

Interesting directions for future research are the study of the cross–gender patterns of occupational persistence, and asymmetric equilibria across occupations. Analyzing the latter would make it possible to capture heterogeneity across occupations, though it requires much richer data in order to reliably estimate the separate channels of persistence at the occupational level.

Chapter 3

Structural Transformation, Innovation and Growth: The Role of Income Distribution

3.1 Introduction

It is a well-known fact that over the last decades countries experienced remarkably different paths of economic development. Structural change[1] – the secular shift of labor and output away from agriculture to manufacturing and services– has been considered one of the key features of development.[2] Recently, the attention of economists and policymakers has been drawn by the outstanding economic performance of countries that performed a rapid catch-up in the living standards such as Korea, Japan, India and China. These countries did so by industrializing and developing a large manufacturing sector. For this reason, several authors and international organizations have argued that a larger degree of structural change (that is, large outflows of labor from agriculture) is indeed what underdeveloped countries lack, therefore implying a direct link between structural change and growth.

This paper challenges that belief, documenting that not all countries that undertook a deep structural change in the last decades experienced also fast growth. We empirically show that the relationship between structural change and growth negatively depends on the level of income inequality. Consistent with this, we develop a model in which a more unequal distri-

[1]Structural change (or structural transformation) is broadly defined as a long–run change in the structure of an economy. In this paper we specifically look at the employment structure, and in particular at the outflow of labor from agriculture.

[2]Kuznets & Murphy (1966) includes structural change as one of the main stylized facts on development. More recently, McMillan & Rodrik (2011) and Duarte & Restuccia (2010) study how the structural change affects productivity dynamics, which is at the heart of differentials of living standards across countries.

bution of income generates a less agriculture–intensive employment structure, but without effectively fostering technological innovation and growth, due to the creation of many different markets of small size.

Working with a sample of 41 countries for the last 50 years, we document that structural change *per se* does not always imply higher growth. Splitting the sample of countries into two groups by the level of income inequality reveals the following: structural change explains growth (in the period 1960-2010) only among low-inequality countries. Interestingly, the structural change phenomenon is very similar across the two groups, both quantitatively (how much labor moved out of agriculture) and qualitatively (in which sectors the labor flew into). When we investigate labor productivity dynamics, we find that it grew at very different rates across the two groups. For instance, agriculture labor productivity grew at 1.68% per year on average in high–inequality countries, while it grew at 3.69% per year in low-inequality countries. Furthermore, similar differences are found in all other sectors in a consistent fashion. These differentials may be due to underlying differences in the innovativeness of firms across these two groups of countries.[3] Consistent with this view, recent cross–country studies on OECD economies show that high inequality is correlated with less innovativeness indeed (see for instance Hopkin *et al.* (2014)).

Motivated by this evidence, we build a model in which income inequality affects the employment structure of the economy as well as the development path of the economy. In particular, a higher level of inequality generates an employment structure which is less agriculture–intensive, besides having a detrimental effect on the innovation process. The latter effect stems out of a demand structure that is not concentrated enough to induce firms to adopt the modern technologies capable of increasing TFP. In our model, preferences feature income non–homotheticity, implying that changes in income will translate into changes in the bundle of the goods consumed by the households. Households have the same sources of income (a balanced portfolio of wages and profits) but differ in their share of total income: the large majority of the population $(1 - \pi)$ are poor households, while the rest of the population π represents rich households. Consumers choose the quantity of the homogeneous good (mapped to the agriculture good) and the amount of varieties (consumed in discrete units) of the differentiated goods (mapped to the manufacturing and services goods, the *modern sector*), ordered along a hierarchy. Poor households consume a strict subset of what rich households consume, in equilibrium. Therefore, the employment structure of the economy is largely determined by how income is distributed, as this shapes both aggregate demand and type of technologies used by firms.

[3]On the relationship between innovation and productivity at the firm–level, see Hall (2011) and Aghion *et al.* (2009).

Technology innovation decisions of firms push the knowledge level of the economy and enhance growth. For the production of each variety in the modern sector, firms have the possibility of updating the technology (allowing them to produce at lower marginal costs), upon payment of a fixed cost. If they do so, then they are granted a lifetime patent for using that specific technology and make profits out of production. As their profits depend on the amount of goods that they will be able to sell, income distribution matters in that it shapes the incentives for innovation. As a consequence, changes in the consumption structure will determine changes in the employment composition of the economy, as firms decide to adopt expensive (but productive) technologies only for those markets which are large enough.

We calibrate the model to the US economy and perform counterfactual experiments with respect to the degree of income inequality. We find that high–inequality economies are characterized by a relatively smaller agriculture sector and substantially worse growth prospects. For instance, doubling the income differentials among rich and poor (from 2 to 4), decreases the equilibrium growth rate of the economy from 2.6 to 1.56%. An increase in inequality implies an increase in the total amount of labor devoted to production, which disproportionately goes into the modern sector (rather than into the agriculture one), as the use of less productive technologies by firms generates the need for more labor (the ratio of agriculture to non–agriculture employment shares drops from 0.122 to 0.116).

Instead, when we vary the weight of the different goods in households' consumption, a decrease in the size of the agriculture sector is accompanied by improvements in the growth performance. An increase in the weight attached to the agriculture good in the utility function from 0.025 to 0.05 generates a large increase in the agriculture to non–agriculture employment shares (it rises from 0.055 to 0.174), along with a drop in the growth rate (from 2.22 to 1.64%).

To sum up, a relatively small agriculture sector may reflect the fact that most of the consumption is in fact devoted to other goods (in which case, this has positive implications for growth), but it may as well be symptomatic of the use of relatively inefficient technologies in the modern sector (in which case, this has negative implications for growth).

Overall, the mechanisms outlined in our model lend a possible explanation to the experience of several Latin American and Sub-Saharan African countries in the last decades, characterized by high levels of income inequality and some degree of structural change that was not accompanied by sustained growth.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. We provide the empirical evidence in Section 3, while Section 4 to 6 are devoted to the model and the quantitative experiments.

3.2 Related Literature

This project is at the intersection of different strands of the literature. On the one hand, the link between income inequality and economic growth is one of the oldest questions in economics; on the other hand, there exists a large literature on structural change and growth;[4] finally, this paper also builds on the seminal contributions of Romer (1989) and Grossman & Helpman (1993), who construct models of R&D and growth.

With respect to the literature on inequality and growth, classical contributions include Barro (2000), Aghion & Williamson (1998), Banerjee & Duflo (2003) and Galor & Moav (2004). This paper is closer to the small literature that looks at the demand side of the relation between inequality and the efficiency level of an economy. Murphy *et al.* (1989) is the first contribution that studies this issue in a static framework, finding that a too dispersed demand for industrial goods triggers less development. Zweimüller (2000) studies a similar framework in a growth context with non–homothetic preferences, finding an ambiguous effect of inequality on growth. More recently, other works have studied the interaction between inequality and innovation, for instance Aghion *et al.* (2015), Jones & Kim (2014) and Hopkin *et al.* (2014). Instead, Auclert & Rognlie (2017) and Auclert & Rognlie (2018) have studied the effect of inequality on total output, via aggregate demand. Differently from these works, the focus of our work is on the dynamic effects of inequality on innovation, that in turn determines the growth rate of the economy. The closest study to this one is Foellmi & Zweimüller (2006), which extends the analysis of Zweimüller (2000) to a context where income inequality has a twofold effect on the incentives for innovation. This paper employs a version of their model with two important twists: first, we allow for the presence of 2 sectors, out of which only one is subject to innovation; second, we model innovation as technological adoption of new productive processes, rather than as production of new goods. Moreover, the emphasis of our analysis is not on the effect of inequality on growth *per se*, but rather on how the degree of income inequality can tilt the relationship between the employment structure of the economy and growth.

Regarding structural change, the literature is divided between papers that emphasize supply or demand factors. Ngai & Pissarides (2005) develop a theory of structural change in which sectoral TFP growth rates differentials are responsible for the movements of labor across sectors, consistently with the early conjecture of Baumol (1967). Opposed to this, several other authors have claimed that instead demand changes are responsible for structural change. For instance, Echevarria (1997), Laitner (2000), Caselli & Coleman II (2001)

[4] A review of the literature on productivity and structural change is in Krüger (2008).

and Gollin (2002) use income non-homotheticity to derive structural change. In their model, individuals, as they get richer, adjust accordingly the expenditure shares on the different goods, ultimately causing a change in the industry structure. Other papers on structural change include Acemoglu & Guerrieri (2006), Matsuyama (2009), Boppart (2014) and Alder *et al.* (2017). [5] The first part of this literature, the one based on TFP differentials, does not look explicitly at the relationship between structural change and growth. Given that movements of labor only depend on the relative movements in TFP growth rates, there is no link between aggregate TFP and structural change. Conversely, models where income effects play a major role imply a positive correlation between growth and structural change. For instance, in Foellmi & Zweimüller (2008), higher growth (which is exogenous) unambiguously generates faster structural change (therefore, a smaller share of the agriculture sector), not consistent with the evidence documented in this paper.

3.3 Data and Suggestive Evidence

We construct a large panel dataset, building from two different sources. Our data on GDP and population over time comes from the Penn World Tables (covering nearly all countries in the world), while the data on the structure of the economies is only available for 41 countries (from Europe, US, Latin America, Asia and Africa) and comes from the 10-Sector Database[6]. Furthermore, we gather data on inequality from the World Income Inequality Database. Throughout the analysis, we maintain a consistent sample composed of all countries and years for which sectoral data is available. The time period spans the post–war period, with some differences across samples and countries. A more accurate description of our data is in Appendix A.

3.3.1 Stylized Facts

First, we look at the relationship between structural change and growth. The left panel of Figure 3.1 reproduces the well–known fact that richer economies have an agricultural sector that is on average smaller in relative terms. This seems to suggest that pulling out labor from agriculture and diversifying the economy is an important driver of good economic performance. In this same spirit, structural change has been advocated several times in order

[5] The majority of these papers study structural change in a closed economy setup, while an emerging literature now looks at how trade affects structural change. For instance, among others see Teignier (2011), Betts *et al.* (2013), and Galor & Mountford (2008) and Uy *et al.* (2013).

[6] This dataset is publicly available at the Groningen Growth and Development Centre.

to guarantee good economic outcomes for underdeveloped economies. Nonetheless, a more accurate analysis actually reveals that the link between structural change and development is quite heterogeneous across countries. We split our sample of countries into two groups: high–inequality and low–inequality countries. In order to do that, we first compute the average value of income inequality (as measured by the Gini Income coefficient) over the period 1960-2010 for each country. Then, we sort the countries according to this value and define "high–inequality" the top 50%[7]. The right panel of Figure 3.1 shows that the relationship between the agriculture employment share and the level of development is lowest in high–inequality countries. In order to quantify the differential across the two groups, we run regressions of log GDP per capita against the agriculture employment share, including country fixed effects. The inclusion of fixed effects controls for different initial conditions and other fixed factors, allowing us to estimate the slope of the relationship depicted in Figure 3.1. As shown in Table 3.1, the estimated coefficient of -3.57 (Column 1) implies that a decrease of 10% in the agriculture employment share is associated with an increase in GDP per capita of about 35.7% in the whole sample. When we estimate this coefficient separately for high–inequality and low–inequality countries (Columns 2 and 3), we find that in the former subsample the estimate drops to -2.35. Conversely, the estimated coefficient for the latter group is -5.42, more than twice as large. The estimates show that in high–inequality countries structural change (outflow of labor from agriculture) is associated to growth to a much lesser extent[8]. One possible concern of these regressions is the bounded support of the explanatory variable, i.e. the fact that countries at a very advanced development level bunch at the lower bound of the support. By construction, this can potentially bias our results. We repeat our estimates keeping in the sample only those observations with at least 10% of the labor force in the agriculture sector, and the results are practically unchanged (see Table 26 in Appendix B).

This same pattern is apparent in Figure 3.2, where we study the correlation between the average growth rate and the total extent of structural change (outflows of labor from agriculture) experienced in the period 1960–2010. Clearly, the correlation only shows up in the subsect of low–inequality countries, whereas it is virtually zero among high–inequality countries. Note that the degree of structural change (that is, the range of the horizontal axis) is substantially similar across the two groups.

Dividing the sample into subgroups is potentially misleading, as these groups of countries might be different in several other dimensions. Therefore, we also run similar regressions to the one estimated in Column 1 of Table 3.1, estimating an interaction term between the

[7]Changing the threshold to 40% or 60% does not alter substantially the results.
[8]Results are robust to dividing the sample in 3 subsamples rather than two (Columns 4 to 6 of Table 3.1).

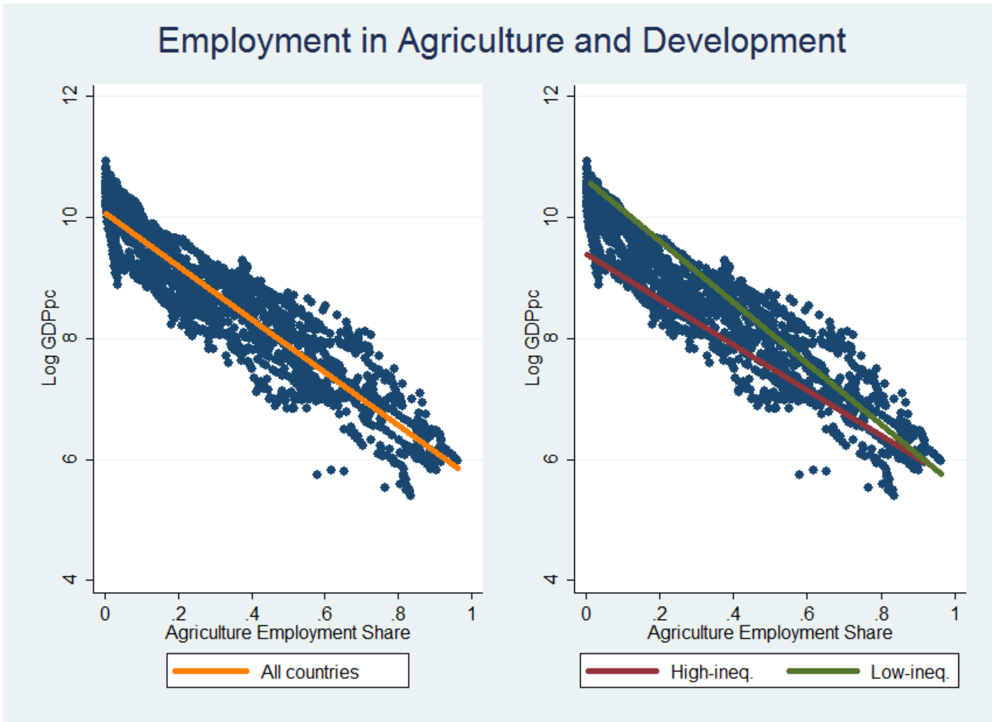

Figure 3.1. Left panel: relationship between log GDP per capita and agricultural employment share. The observation unit is country per year. Right panel: relationship between average yearly economic growth and structural change over the period 1960-2010 (Source: Penn World Tables, ASD, 10SD).

	Dependent Variable: Log GDP per capita					
	(1)	(2)	(3)	(4)	(5)	(6)
	All Sample	Top 50%	Bottom 50%	Bottom 33%	Middle	Top 33%
Agr. Emp. Share	-3.571***	-2.351***	-5.419***	-2.353***	-2.965***	-5.547***
	(0.060)	(0.071)	(0.070)	(0.071)	(0.127)	(0.077)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2099	1056	1043	714	658	727
R^2	0.635	0.517	0.856	0.613	0.458	0.879
Number of Countries	41	21	20	14	13	14

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1. Linear Regression of log GDP per capita against agriculture employment share. The coefficient is estimated separately for the whole sample (column 1) and for different parts of the distribution of countries by income inequality in the period 1960-2010 (columns 2 to 6).

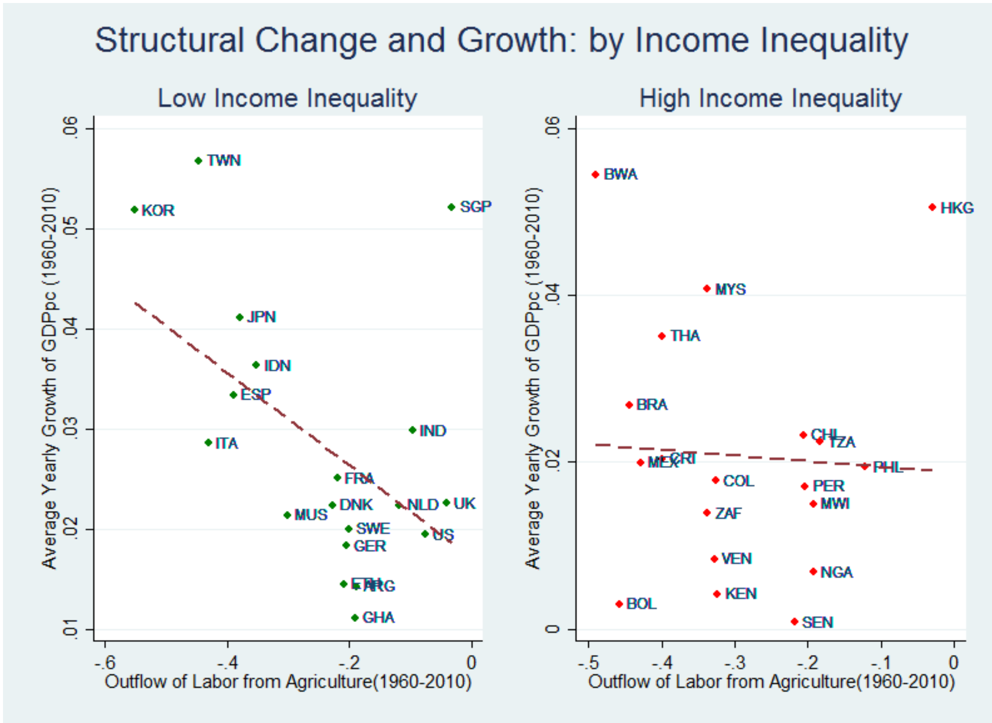

Figure 3.2. Relationship between average yearly economic growth and structural change for two groups of countries: high–inequality and low–inequality. (Source: Penn World Tables, 10SD).

agriculture employment share and an indicator for belonging to the top 50% of inequality. The results (shown in Table 26 in Appendix B) are perfectly in line with our previous findings: high concentration of income substantially weakens the correlation between structural change and growth. This result is robust to the inclusion of year fixed effects (controlling for common trends across countries) and other controls such as: size of the country, degree of openness, composition of GDP (consumption, investment and public expenditure) and dependence on natural resources.

A possible hypothesis is that the structural change of high–inequality and low–inequality countries had a different impact on growth because in fact they were quite different phenomena from a qualitative point of view. So far we have controlled only for the outflow of labor from agriculture, without saying anything on which sector that labor force flew into. In particular, one possibility is that labor was entering the manufacturing sector (which is a high–productivity sector) in low–inequality countries, whereas it was entering comparatively more in the services sector (which is a low productivity sector) in high–inequality countries. In Figure 3.3, we plot the cumulative inflow of labor into the manufacturing sector over time. The figure reveals that the extent of structural change that interested the manufacturing sector is comparable across the two groups of countries. In particular, the average cumulative gross inflow is practically identical, and also the two distributions are very similar. We also compute the cumulative inflow and outflow rates for each of the 10 sectors over the time period, and the patterns are remarkably similar across the two groups (we report the results in Appendix B, Table 27).

Figure 3.3. Cumulative inflow of labor into the Manufacturing sector, by natural resources abundance (Source: Penn World Tables, ASD, 10SD).

Next, we study the behavior of labor productivity –as measured by value added per worker– over time. We perform the exercise at the sectoral level, in order to shed light on what are the sectors in which the high–inequality economies are falling behind. Table 3.2 shows very large differentials in the growth rates of labor productivity between the two groups[9].

Table 3.2. Average Yearly Labor Productivity Growth Rates, by Income Inequality Group.

Sector	**High Inequality**	**Low Inequality**
Agriculture	1.62	3.55
Manufacturing	1.88	3.52
Services	0.47	1.74

The differentials are relevant and significant in all macro sectors of the economy (Agri-

[9]A similar table for the 10 sectors is reported in Appendix B.

culture, Manufacturing, Services). Furthermore, we do not find any relevant asymmetries in this comparison between manufacturing and services. This observation will lead us to postulate a model of 2 sectors only, abstracting from differences between manufacturing and services. In the next section we outline an endogenous growth model through which we aim to explain the data patterns presented so far.[10]

3.4 The Model

This model is an adaptation of the model by Foellmi & Zweimüller (2006) with two main twists: first, we allow for the existence of an homogeneous good sector, mapped to the agriculture sector (in order to study structural change); second, we assume that technological progress in the modern sector takes place through process adoption rather than product innovation. The numeraire of the economy is the homogeneous good, therefore we assume that $P_a(t) = 1 \; \forall \, t$.

3.4.1 Demand side

Consider an economy in which an homogeneous good and many differentiated products are produced. At each time t, households choose a quantity C_a of the homogeneous good and which differentiated goods $j \in [0, \infty)$ to consume. Differentiated goods are ranked in the utility function of agents, such that goods more on the left in the hierarchy are needed more urgently.[11] We assume that the differentiated goods problem is a "yes or no" decision: $C_j \in \{0, 1\}$. We model the hierarchy by assuming that C_j units of good j yield utility $v(C_j)\xi(j)$. We normalize the baseline utility, such that $v(C_j) = C_j$. Also, we assume that the weighting function takes the form $\xi(j) = j^{-\gamma}$.

Households solve the following intertemporal problem:

$$\max_{\{C_a(t), \{C_j(t)\}_{j=0}^{\infty}\}_{t=0}^{\infty}} \; U = \int_0^{\infty} \frac{1}{1-\sigma} \left[(C_a(t))^{\alpha} \left(\int_0^{\infty} j^{-\gamma} C_j(t) dj \right)^{1-\alpha} \right]^{1-\sigma} e^{-\rho t} dt \qquad (3.1)$$

$$s.t. \qquad \int_0^{\infty} \left[C_a(t) + \int_0^{\infty} C_j(t) P_j(t) dj \right] e^{-R(0,t)} dt \leq \int_0^{\infty} I(t) e^{-R(0,t)} dt + V_0 \qquad (3.2)$$

[10] In our model the employment shares will not be determined by different TFP dynamics, an element from which we abstract. In the Appendix, consistent with the literature, we argue that differentials in TFP growth rates cannot be the only determinant of structural change.

[11] In order to simplify the rest of the analysis, we assume that households never want to consume a given good j unless they are consuming all goods $j^{'<j}$ (Assumption U_C). This greatly simplifies the equilibrium pricing scheme without altering the qualitative predictions of our model. We also work out the equilibrium without Assumption U_C in the Appendix.

where $R(0,t) = \int_0^t r(s)ds$ is the cumulative discount rate between 0 and t, $I(t)$ is total income (wages, profits and rents) at time t, and V_0 is initial wealth.
Defining $u(t) = \left[(C_a(t))^{\alpha}\left(\int_0^{\infty} j^{-\gamma}C_j(t)dj\right)^{1-\alpha}\right]$, the FOCs of the households' problem read as follows:

$$(C_a): \qquad u(t)^{-\sigma}\alpha(C_a(t))^{\alpha-1}\left[\int_0^{\infty} j^{-\gamma}C_j(t)dj\right]^{1-\alpha} e^{-\rho t} = \lambda e^{-R(0,t)} \tag{3.3}$$

$$(C_j): C_j = \begin{cases} 1 & \text{if } u(t)^{-\sigma}(1-\alpha)(C_a(t))^{\alpha}\left[\int_0^{\infty} j^{-\gamma}C_j(t)dj\right]^{-\alpha} j^{-\gamma}e^{-\rho t} \geq \lambda P_j(t)e^{-R(0,t)} \\ 0 & \text{otherwise} \end{cases} \tag{3.4}$$

The LHS of inequality 3.4, after dividing both sides by λ, can be interpreted as the willingness to pay for a discrete unit of good j. Notice that this amount is decreasing over j: this means that, *ceteris paribus*, households are willing to spend more for goods that are more urgent to them (more on the left in the hierarchy). Also, the willingness to pay depends on the income level, that is on the marginal utility of wealth λ. The higher the latter, the less households are willing to spend: this implies that rich households (which will have a smaller λ) are willing to spend more than poor households.

3.4.2 Income Distribution

We assume that income is unequally distributed. There are two classes of individuals in the economy: rich individuals represent a share π of the population, while poor individuals represent the remaining $1-\pi$. Let $I_k(t)$ be total income of household k at time t. Let $C_a^k(t)$ and $N_k(t)$ be respectively the amount of homogeneous good and the last differentiated good consumed by household k, with $k \in \{R, P\}$. We assume that households own a balanced portfolio of wages and profits, and that rich household own a larger share of total income, that is $I_R(t) = \theta I_P(t)\ \forall\, t$, with $\theta > 1$. The income distribution can be thought as being generated by differences in the capability of supplying labor efficiency units to the market. Notice that in our setup the Lorenz curve is piecewise linear and standard measures of inequality, such as the Gini coefficient, are increasing in the parameter θ (Figure 3.4).

3.4.3 Supply Side

Let $A(t)$ be the technology level of the economy. In the agriculture sector production takes place according to a linear technology, that transforms $\frac{\chi}{A(t)}$ units of labor into 1 unit of output. In the modern sector, instead, there exist two different technologies for producing each single good: an old (constant returns to scale) technology, available to everybody at no

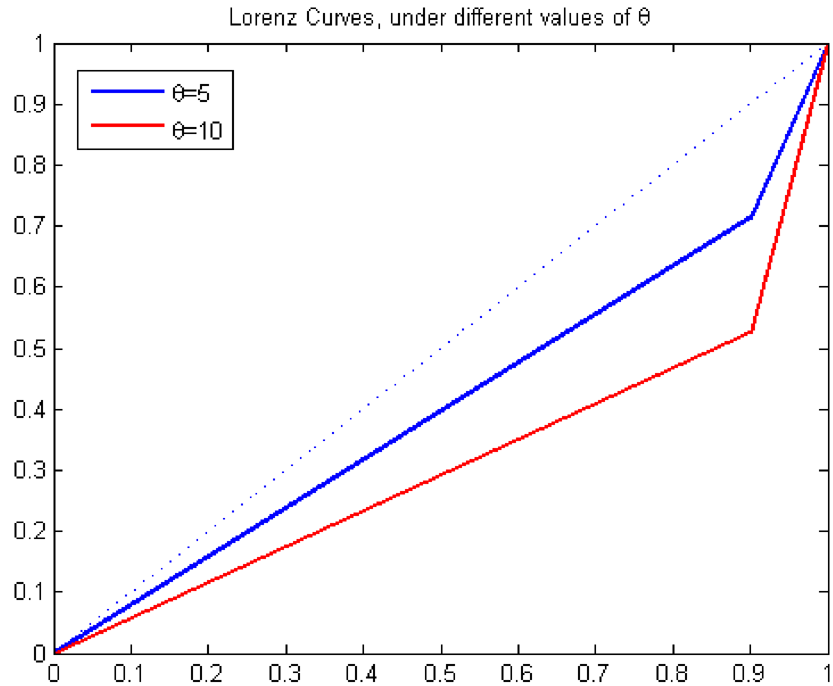

Figure 3.4. Lorenz Curves under different values of θ and fixed value of $\pi = 0.1$

cost, according to which it is possible to produce 1 unit of output with $\frac{\psi^O}{A(t)}$ units of labor; and a new (increasing returns to scale) technology, available upon the payment of a fixed cost $\frac{F}{A(t)}$ in labor units[12], that allows to produce 1 unit of output with $\frac{\psi^N}{A(t)}$ units of labor, with $\psi^N < \psi^O$. A producer adopting the new technology is free to set the price and decide how much quantity to produce. However, his decisions are constrained by free-entry of firms and by the presence of a competitive fringe that can produce with the CRS technology.

Agriculture Sector

Consider the maximization problem of a firm operating in the agriculture sector:

$$\max_{L_a(t)} \quad \frac{A(t)L_a(t)}{\chi} - w(t)L_a(t) \tag{3.5}$$

The FOC of this problem is:

$$\frac{1}{\chi} = \frac{w(t)}{A(t)} \tag{3.6}$$

[12]Even though the nominal units of the fixed cost are decreasing in $A(t)$, the cost in real terms will stay constant, as in equilibrium the wage will also be increasing at the same rate as $A(t)$. Importantly, as relative price and the ratio between the wage and A grow at the same rate in equilibrium, an interior solution to the technology adoption problem of firms is ensured (this is a necessary condition, as in our setup profits are bounded).

Notice that from equation 3.6 it follows that $w(t)$ and $A(t)$ must grow at the same rate in equilibrium. The intuition is that all advances in technology have a positive effect on labor productivity and in a competitive framework this produces an increase in wages of the same amount.

Modern Sector

Old Technology

$$\max_{L_j^O(t)} \quad P_j(t)\frac{A(t)L_j^O(t)}{\psi^O} - w(t)L_j^O(t) \tag{3.7}$$

As this technology is available to everybody, whenever it is used,

$$\frac{P_j(t)}{\psi^O} = \frac{w(t)}{A(t)} \tag{3.8}$$

Wage equalization across sectors and Equation 3.6 imply that $P_j(t) = \frac{\psi^O}{\chi}$. This is the price that will be charged by the competitive fringe in equilibrium for any good j, if it operates.

Modern Technology

When a firm pays the fixed cost $\frac{F}{A(t)}$ in labor units, it has access to the following technology:

$$Y_j^N(t) = \frac{A(t)}{\psi^N}L_j^N(t) \tag{3.9}$$

We assume that upon payment of the fixed cost, the firm receives a lifetime patent on the technology. As the technology developed allows the producer to produces at lower marginal costs than the competitive fringe, in equilibrium he will become a monopolist. The monopolist has now the possibility of setting the price and decide how much quantity to produce.

Consider first the price setting problem. Remember that the monopolist is constrained by the competitive fringe that is willing to produce any quantity at price $\frac{\psi^O}{\chi}$. Therefore, the price set by the monopolist cannot exceed that level in any case. The demand faced by the monopolist reads as follows:

$$Q_j(t)\begin{cases} = 0 & \text{if } P_j(t) > \psi^O \frac{}{\chi}. \\ \in [0, Q_j^{max}(t)] & \text{if } P_j(t) \leq \psi^O \frac{}{\chi}. \end{cases} \tag{3.10}$$

where $Q_j^{max}(t)$ is the maximum size of the market, which is the amount of goods produced by the competitive fringe at time t, before the entry of the monopolist.

It is trivial to see that whenever the producer is willing to produce any quantity, then he will want to serve all the market. At the same time, it will not always be the case that the monopolist wants to produce. In order to decide whether to enter the market, firms evaluate the infinite stream of profits coming from being the monopolist in the production of a particular good[13].

Suppose that the competitive fringe is serving the market j, and that a prospective monopolist is considering to enter the market, innovating the production process. The value of the technology adoption for good j at time t (which we denote $V_j(t)$) is given the optimized value of discounted profits:

$$V_j(t) = \max_{\{P_j(s),Q_j(s)\}} \int_t^{\infty} \Pi_j(s)e^{-R(s,t)}ds = \max_{\{P_j(s),Q_j(s)\}} \int_t^{\infty} \left(P_j(s) - \frac{\psi^N}{A(t)}w(t)\right) Q_j(s)e^{-R(s,t)}ds \tag{3.11}$$

where $Q_j(s)$ has to be consistent with Equation 3.10. Trivially, when the value of technology adoption is larger than its cost (that is, $V_j(t) \geq F\frac{w(t)}{A(t)}$), it is profitable for the monopolist to enter the market and start the production. Free entry implies that whenever an innovation is to be made, discounted profits (Equation 3.11) are exactly equal to the cost of innovation.

3.4.4 Innovation and Technology

The level of technology of the economy A is defined as the mass of modern technologies that are adopted at a given point in time. This reflects the idea that technology adoption by firms have spillover effects on the whole modern sector. In turn, this raises labor productivity for the production of modern sector goods.

$$A(t) = \int_0^{\infty} \mathbb{1}\left\{Y_j^N(t) > 0\right\} dj \tag{3.12}$$

The rate at which $A(t)$ grows depends on $L_R(t)$, the amount of workers who are employed in the research sector, developing new technologies.

$$\dot{A}(t) = L_R(t)\left(\frac{A(t)}{F}\right) \tag{3.13}$$

[13] Whenever there are changes in the price and/or in the market size, it is crucial to know the time at which these changes occur. This implies that growth rates of the variables are necessary in order to compute profits.

The previous equation reflects the idea that technology raises labor productivity also in the research sector. Another way of interpreting equation 3.13 is to multiply both sides by $\frac{F}{A(t)}$: the labor demanded in the research sector is the product of a measure of the mass of goods that have technological adoption at a given time t (which is $\dot{A}(t)$) and the labor employed in each of these goods $\left(\frac{F}{A(t)}\right)$. The latter term is decreasing over time, meaning that for a given technological innovation you need less and less labor.

3.4.5 Equilibrium Definition

Definition 5. *Equilibrium An equilibrium for this economy is a sequence of allocations for the households* $\{C_a^P(t), C_a^R(t), \{C_j^P(t), C_j^R(t)\}_{j=0}^{\infty}\}_{t=0}^{\infty}$*, allocations for the firms* $\{L_A(t), \{L_j^O(t), L_j^N(t)\}_{j=0}^{\infty}, L_R(t)\}_{t=0}^{\infty}$*, prices* $\{\{P_j(t)\}_{j=0}^{\infty}, w(t), r(t)\}_{t=0}^{\infty}$ *and a sequence of technology levels* $\{A(t)\}_{t=0}^{\infty}$ *such that:*

- *given prices, the allocations for the households solves their dynamic problem;*
- *given prices and technology level* $A(t)$*, the allocations for the firms solves their problem at each time* t*;*
- *the technology level* $A(t)$ *is defined by equation 3.12 and evolves according to equation 3.13;*
- *markets clear at each time* t*:*

$$Y_a(t) = \frac{A(t)}{\chi} L_a(t) = (1-\pi)C_a^P + \pi C_a^R \tag{3.14}$$

$$Y_j^O(t) + Y_j^N(t) = \frac{A(t)}{\psi^O} L_j^O(t) + \frac{A(t)}{\psi^N} L_j^N(t) = (1-\pi)C_j^P(t) + \pi C_j^R(t) \qquad \forall\ j \tag{3.15}$$

$$L_A(t) + \int_0^{\infty} L_j(t)dj + L_R(t) = L \tag{3.16}$$

where $L_j(t) = L_j^O(t) + L_j^N(t)$*.*

3.4.6 Equilibrium Characterization

Lemma 6 (Consumption follows the hierarchy)**.** *In equilibrium, each type of household consumes a continuous measure of varieties* $[0, N_k]$*. Furthermore,* $N_P(t) < N_R(t)$*.*

Proof. See Appendix. □

Intuitively, households expand their consumption basket gradually. Given that the supply side is symmetric across goods, it cannot be the case that households decide to consume some good j if they do not consume all other goods that are higher up in the hierarchy. Moreover, given that the incentives for savings are the same across households types, the rich ones will consume a larger set of differentiated goods. Given that these goods are consumed in discrete units, this imply that poor households consume in equilibrium a subset of the goods consumed by the rich, as shown in Figure 3.6.

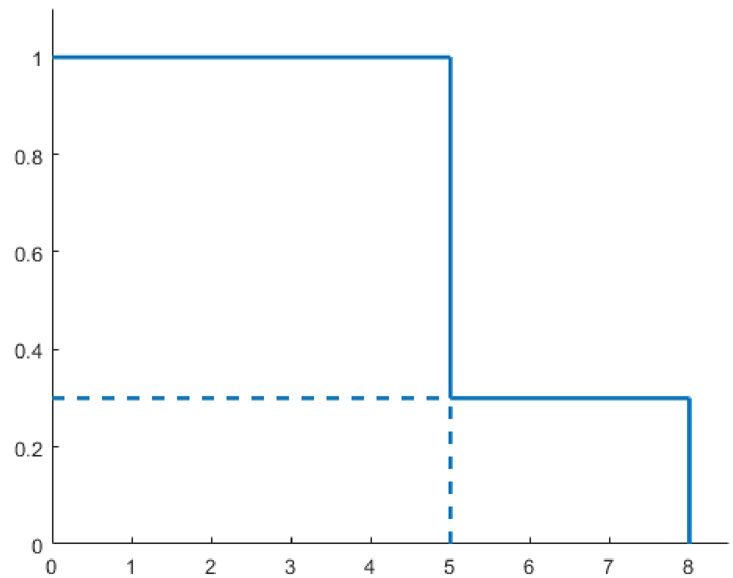

Figure 3.5. Equilibrium demand of differentiated goods. $N_P = 5$, $N_R = 8$, $\pi = 0.3$.

Figure 3.6 plots the quantity consumed of each differentiated good in equilibrium. Everybody in the economy consumes up to good $N_P(t)$, and then the rich will consume a positive mass of additional goods, equal to $N_R(t) - N_P(t)$. Note that when the consumption follows the hierarchy, then the expression $\int_0^\infty j^{-\gamma} C_j(t) dj$ simplifies to $\frac{N(t)^{1-\gamma}}{1-\gamma}$.

Turning to the supply side, the first thing we establish is that for each good only one of the two technologies will be employed at a given point in time. This follows from the fact that the new technology allows to produce at lower marginal costs than the technology of the competitive fringe. Therefore, the producer owner of the new technology will price the competitive fringe out.

Lemma 7 (No Coexistence of Both Technologies)**.** *For each good j, all the amount consumed at each given point in time t, is entirely produced either with the old or with the new technology.*

Proof. See Appendix. □

Now we study equilibrium prices. As the willingness to pay for good j is higher than the willingness to pay for j', with $j' > j$, it must be the case that also technology adoption follows the hierarchy. Denote by $j^*(t)$ the last good for which the new technology is adopted at time t.

Monopolists have no incentives in fixing strategically the prices in order to attract more consumers, as demand would not react at all. Therefore, it is optimal for producers to fix prices at the highest possible level.

Lemma 8 (Equilibrium Pricing)**.** *Equilibrium prices are flat: $P_j(t) = \frac{\psi^O}{\chi} \qquad \forall j$.*

Under a flat equilibrium pricing, profits are a step-function:

$$\Pi_j(t) = \begin{cases} \frac{\psi^O - \psi^N}{\chi} & \text{if } j \leq N_P \\ \frac{\psi^O - \psi^N}{\chi}\pi & \text{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{3.17}$$

We can note that profits are only a function of the quantity sold (*market size*). In particular, they jump at the moment in which the good starts to be sold to the whole population. Using equilibrium profits, we can write an expression for the value of innovation in each single good market. It corresponds to the infinite stream of discounted profits accruing from the technological adoption. The expression for $V_j(t)$ reads as follows:

$$V_j(t) = \begin{cases} \frac{\psi^O - \psi^N}{\chi} \int_t^{\infty} e^{-R(s,t)} ds & \text{if } j \leq N_P(t) \\ \frac{\psi^O - \psi^N}{\chi} \left[\int_t^{t+\Delta_j^M(t)} \pi e^{-R(s,t)} ds + \int_{t+\Delta_j^M(t)}^{\infty} e^{-R(s,t)} ds \right] & \text{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{3.18}$$

, where $\Delta_j^M(t)$ is the waiting time for market j to become a mass market. The value $V_j(t)$ is constant for all goods which are consumed by the whole market, reflecting the fact that prices and quantities are constant. Above the level N_P, the value of innovation starts to decrease in a continuous fashion: the further away j is from N_P, the longer the producer will need to wait in order to sell to the whole market.

Lemma 9. *Innovation Values $V_j(t)$ is a continuous and decreasing function of j, $\forall t$. An equilibrium in which $\exists\, j \mid Y_j^O > 0$ and $\exists\, j' \mid Y_j'^N > 0$ (there is neither no adoption nor full adoption of modern technologies) must be such that $j^* \geq N_P$.*

Proof. See Appendix. □

Now we turn again to the households' optimal choices. First of all, we note that both types of household consume the same proportion of the two goods (agriculture and the one from the modern sector). This is an implication of Cobb–Douglas preferences, along with the flat pricing.

Lemma 10 (Optimal Consumption of Differentiated Goods)**.** *In equilibrium, Equation 3.4 must hold with equality for both types of households.*

Proof. See appendix. □

Thus, taking the ratio between 3.3 and 3.4 (for good $N(t)$, for which it is binding) yields:

$$\frac{\alpha}{1-\alpha}\frac{1}{1-\gamma}\frac{N_k(t)}{C_a^k(t)} = \frac{1}{P_{N_k}(t)} \qquad k \in \{P, R\} \tag{3.19}$$

Equation 3.19, together with the constancy of relative prices, implies that the mass of differentiated goods consumed grows at the same rate as this new variable. We define this rate as $g_c(t)$:

$$g_c^k(t) = \frac{\dot{C}_a^k(t)}{C_a^k(t)} = \frac{\dot{N}_k(t)}{N_k(t)} \tag{3.20}$$

In turn, consumption growth rates depend on the interest rate (incentives for savings). To see this, first we take logs of equation 3.3, obtaining the following expression:

$$\begin{aligned} &-\sigma(\alpha\log(C_a^k(t)) + (1-\alpha)(1-\gamma)(\log(N_k(t)) - \log(1-\gamma)) + (\alpha-1)\log(C_a^k(t)) + \\ &\qquad + (1-\alpha)(1-\gamma)(\log(N_k(t)) - \rho t = \log(\lambda) - \int_0^t r(s)ds \end{aligned} \tag{3.21}$$

Now, taking derivatives with respect to time, and using the fact that $C_a^k(t)$ and $N_k(t)$ grow at the same rate, we can pin down the interest rate. In the following we omit the index k in the growth rate of consumption $g_c^k(t)$, given that households face the same interest rate and therefore their consumption streams must grow at the same rate:

$$[\sigma\alpha + \sigma(1-\alpha)(1-\gamma) + \gamma(1-\alpha)]g_c(t) = r(t) - \rho \tag{3.22}$$

3.5 Balanced Growth Path

The rest of the analysis focuses on a Balanced Growth Path equilibrium, in which all variables grow at a constant rate. From equation 3.22 it is clear that when the consumption growth rate is constant ($g_c(t) = g_c \,\forall\, t$), the interest rate will also be constant: $r(t) = r \,\forall\, t$. On a balanced growth path, the value of technological adoptions has a closed form. First, note that on such a path it is possible to solve exlicitely for the waiting time $\Delta_j^M(t)$. $N_P(t)e^{g_c \Delta_j^M(t)} = j$ implies that $\Delta_j^M(t) = \frac{\log\left(\frac{j}{N_P(t)}\right)}{g_c}$, where g_c is the constant growth rate of N_P. The waiting time is increasing in the distance between N_P (the frontier of mass goods) and j, and decreasing in the rate of growth of such frontier. Second, substituting the fixed interest rate into equation 56, and plugging in the expression for the equilibrium prices from equation 50, it is now possible to solve the integrals.

Thus, the expression simplifies further to:

$$V_j(t) = \begin{cases} \frac{\psi^O - \psi^N}{\chi}\frac{1}{r} & \text{if } j \leq N_P(t) \\ \frac{\psi^O - \psi^N}{\chi}\left(\pi \frac{e^{-r\Delta_j^M(t)} - 1}{-r} + \frac{e^{-r\Delta_j^M(t)}}{r}\right) & \text{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{3.23}$$

The quantity sold starts at π, for those goods between N_P and N_R, and then jumps to 1 after a period of time $\Delta_j^M(t)$.

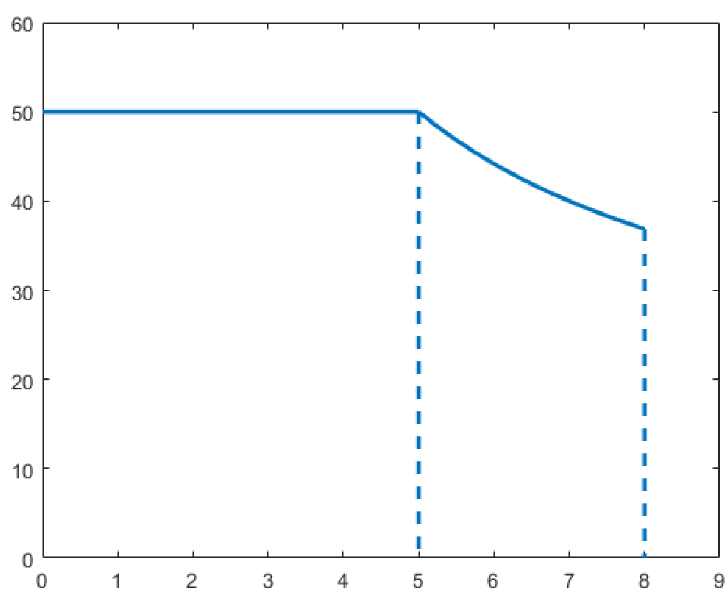

Figure 3.6. Value of Innovation for differentiated goods. $N_P = 5$, $N_R = 8$, $\pi = 0.3$, $\frac{\psi^O - \psi^N}{\chi} = 0.5$, $r = 0.01$.

Now, we derive a system of equations that characterizes the balanced growth path of our model economy. The endogenous variables of this model are 10: C_a^P, C_a^R, N_P, N_R, r, g_c, g_A, A, Δ_A^M. One level will have to be normalized, and then we can interpret the other ones in terms of ratios to the normalized one. We choose to normalize A to 1.
The long–run equilibrium is characterized by the following system of equations (from which we omit the time index t):

(Consumption Allocation of poor, from equation 3.19)

$$\frac{\alpha}{1-\alpha}\frac{1}{1-\gamma}\frac{N_P}{C_a^P} = \frac{\chi}{\psi^O} \tag{3.24}$$

(Consumption Allocation of rich, from equation 3.19)

$$\frac{\alpha}{1-\alpha}\frac{1}{1-\gamma}\frac{N_R}{C_a^R} = \frac{\chi}{\psi^O} \tag{3.25}$$

These two equations are derived from the FOCs of the households and represent the optimal consumption allocation. Note that households consume the two consumption items in the same proportions (in other words, preferences are homothetic across types of consumption goods).

(Euler Equation, from equation 3.22)

$$[\sigma\alpha + (1-\alpha) + (\sigma-1)(1-\alpha)(1-\gamma)]g_c = r - \rho \tag{3.26}$$

(Free-Entry Condition, from equation 56)

$$\frac{\psi^O - \psi^N}{\chi}\left(\pi\frac{1-e^{-r\Delta_A^M}}{r} + \frac{e^{-r\Delta_A^M}}{r}\right) = \frac{F}{\chi} \tag{3.27}$$

This expression equates expected profits from innovation to its cost. Given g and r, it finds the equilibrium ratio between A and N_P, i.e. the distance between the technological frontier and the last good consumed by the poor.

(Definition of Delta in a BGP)

$$\Delta_A^M = \frac{\log\left(\frac{A}{N_P}\right)}{g_c} \tag{3.28}$$

This follows from the definition of Δ_j^M, for the specific good on the technological frontier ($j = A$). It says that the waiting time for the marginal good (for which the technology is being upgraded) to become a mass good is increasing in the distance between A and N_P and decreasing in the growth rate of consumption g_c.

(Constancy of Δ_A^M)

$$g_c = g_A \tag{3.29}$$

This equation guarantees that Δ_A^M is constant (see equation 3.28). This means that technology must grow at the same level of consumption, on a BGP.

(B.C. of poor)

$$\frac{C_a^P + N_P\frac{\psi^O}{\chi}}{g_c - r} = \frac{\frac{A}{\chi} + N_P(\frac{\psi^O - \psi^N}{\chi}) + (A - N_P)(\frac{\psi^O - \psi^N}{\chi})\pi - \frac{Fg_c}{\chi}A}{(g_c - r)(\pi\theta + (1 - \pi))} \tag{3.30}$$

(B.C. of rich)

$$\frac{C_a^R + N_R\frac{\psi^O}{\chi}}{g_c - r} = \theta\frac{\frac{A}{\chi} + N_R(\frac{\psi^O - \psi^N}{\chi}) + (A - N_P)(\frac{\psi^O - \psi^N}{\chi})\pi - \frac{Fg_c}{\chi}A}{(g_c - r)(\pi\theta + (1 - \pi))} \tag{3.31}$$

These last two equations are the budget constraints solved for on the BGP. Total expenditures (in the LHS) are equated to the total income stream (RHS), which is composed of wages ($\frac{A}{\chi}$) and profits net of payment of the fixed costs. Note that A can be interpreted as the actual level of the technology in the very first period of BGP. As already mentioned, we normalize it to 1 in our simulations.

3.6 Quantitative Analysis

In this section we perform our quantitative analysis. First, we need to parametrize our economy. Second, we will study the effect of inequality on the growth rate of the economy in the long–run equilibrium. Moreover, we study the relationship between the relative size of the agriculture sector and the growth performance, with a focus on how differentials in inequality might affect this relationship. We will then be able to assess whether our model is able to rationalize the empirical evidence presented earlier in this paper.

3.6.1 Calibration

This model has a total of 10 parameters to be calibrated. One period in the model corresponds to 1 year. In the baseline calibration we pick parameter values so that our model economy in BGP matches some features of the US economy.

Preferences are characterized by the following parameters: α, γ, σ, and ρ. We calibrate $\sigma = 5$ (intertemporal elasticity of substitution) and $\rho = 0.015$ (household discount factor), following the literature (Mehra & Prescott (1985)). The two remaining parameters α and γ are calibrated to match the consumption expenditure share in agriculture in the US in 2005 (from the International Programme Comparison of the World Bank) and the average growth rate of the US economy in the period 1960-2010 (from the World Penn Tables).

The technology parameters are: χ, ψ^O, ψ^N and F. The agriculture labor productivity χ is normalized to 1. The parameters ψ^N and ψ^O regulate the difference in productivity of the traditional and modern technology. Following Midrigan & Xu (2010), we choose ψ^N as to replicate a TFP differential of 40%[14] between modern and traditional technology firms. The parameter ψ^O is then chosen to match the relative productivity of non–agriculture sector to the agriculture sector. We match the relative VA per worker of the rest of the economy to the agriculture sector in the US in the year 2005 (from the 10-Sector Database). The fixed cost of innovation F is calibrated as to match the interest rate.

Finally, in the baseline calibration we set $\pi = 0.1$ and we calibrate θ as to match the share of total income held by the top 10%.

Table 3.3 summarizes the calibrated parameter values, together with the targets used.

[14] In their paper, this number implies a relative size of producers in modern to traditional sectors which is in line with Hsieh & Klenow (2012).

Table 3.3. Baseline Calibration. Values of Parameters and Targets.

Preferences Parameters

Parameter	Description	Value	Target	Data	Model
α	Weight of Agr.Good in the Utility	0.052	Cons. Exp. Shares	0.089	0.089
γ	Weighting factor of varieties	0.388	Growth Rate	0.019	0.019
σ	Intertemporal elasticity of substitution	1.5	Mehra & Prescott (1985)	-	-
ρ	Time discount Factor	0.015	Mehra & Prescott (1985)	-	-

Technology Parameters

Parameter	Description	Value	Target	Data	Model
ψ^O	Old Technology Parameter	1.058	Relative VA per worker	1.07	1.07
ψ^N	New Technology Parameter	0.755	Midrigan & Xu (2010)	-	-
χ	Agr. Technology Parameter	1	Normalization	-	-
F	Fixed cost	5.143	Interest Rate	0.04	0.04

Income Distribution Parameters

Parameter	Description	Value	Target	Data	Model
π	Share of Rich	0.1	-	-	-
θ	Rich to Poor Income Ratio	3.33	Share of income held by top 10%	0.27	0.27

3.6.2 Effect of Inequality on Long–Run Growth

We simulate our model economy under the baseline parametrization, and the experiment we perform involves changing the value of θ.[15] Table 3.4 shows how changes in the inequality impact the long–run equilibrium. Mechanically, an increase in inequality leads poor households to consume less and rich households to consume more. Changes in consumption do not have any impact in the consumption composition, as in this economy Engel curves across types of goods are linear. The increasing distance between A and N_P makes innovation less attractive, so that both the interest rate r and the growth rate g drop. Both of these effects determine an increase in the waiting time Δ_A^M. Income concentration generates a large number of small markets that do not provide strong incentive for innovation to firms. Furthermore, all goods produced in the exclusive markets $[A,N_R]$ employ relatively more labor (as they are produced with the old technology), and by doing so they take resources away from investment in technology. Figure 3.7 shows that the growth rate of the economy is monotonically decreasing in the degree of income inequality.

θ	C_a^P	C_a^R	N_P	N_R	A	Δ_A^M	r	g
2	0.085	0.170	0.901	1.801	1	4.02	0.0493	0.0260
3	0.078	0.235	0.832	2.496	1	8.89	0.0422	0.0207
4	0.073	0.292	0.775	3.101	1	16.34	0.0355	0.0156
5	0.069	0.345	0.733	3.667	1	33.97	0.0270	0.0091

Table 3.4. Simulations of the BGP, under the baseline parametrization. Impact of changes in inequality (θ) on the long–run equilibrium.

[15] The Gini index is unambigously growing in θ, whereas the same is not true for π. This is the reason why our exercises will only involve changes in θ.

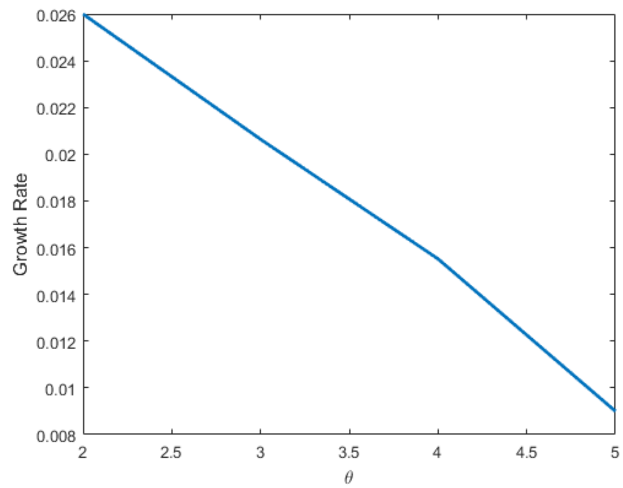

Figure 3.7. Effect of Inequality on Long–Run Growth, under the baseline calibration.

3.6.3 Effect of Inequality on Employment Shares

After establishing that inequality has a negative effect on growth, we now turn to study how it affects the employment shares of the economy. Using the production function, we can express the employment shares in terms of consumption:

$$L_a(t) = (1-\pi)C_a^P + \pi C_a^R \frac{\chi}{A(t)} \tag{3.32}$$

$$L_M(t) = \int_0^\infty L_j(t)dj = N_P(t)\frac{\psi^N}{A(t)} + (A(t) - N_P(t))\frac{\psi^N}{A(t)}\pi + (N_R(t) - A(t))\frac{\psi^O}{A(t)}\pi \tag{3.33}$$

Intuitively, the employment shares directly reflect the division of consumption across sectors, increasing when more consumption is allocated to a specific sector. Nonetheless, another crucial aspect is which technologies are employed in the modern sector. In particular, fixing the consumption shares across sectors, the less the modern technology is used (that is, the higher the distance between N_R and A, or the higher the π), the more labor is allocated -with respect to agriculture- to the modern sector. Thus, as it is apparent from Table 3.5 and Figure 3.8, an increase in θ causes a reallocation of labor from agriculture to the modern sector. At the same time, both shares grow in absolute terms, as the amount of labor devoted to the research sector (the one producing innovation) falls with θ, for the reasons we saw in the previous section.

Note that these movements in the employment shares are not caused by changes in

θ	L_A	L_M	$\frac{L_A}{L_M}$	g
2	0.094	0.772	0.122	0.0260
3	0.095	0.799	0.118	0.0207
4	0.096	0.825	0.116	0.0156
5	0.097	0.856	0.114	0.0091

Table 3.5. Simulations of the BGP, under the baseline parametrization. Impact of changes in inequality (θ) on the long–run equilibrium.

consumption shares. A change in θ does not reallocate consumption from a sector to another, but instead it only alters the share of modern goods produced with the modern technology as opposed with the old one. In the next subsection we investigate how the long–run equilibrium changes when consumption shares themselves change.

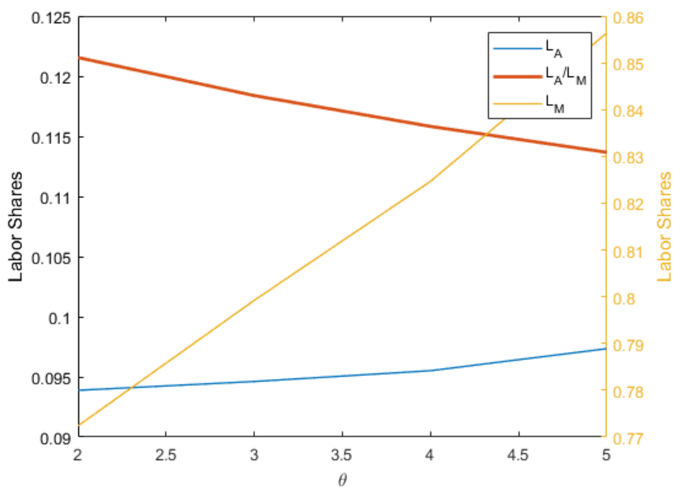

Figure 3.8. Effect of Inequality on Employment Shares, under the baseline calibration.

3.6.4 Effect of α on Employment Shares

Performing a comparative static exercise w.r.t. α is instructive, as it allows us to understand how the equilibrium changes when the weights on the different consumption goods change. As it is intuitive, an increase in α (that is, an increase in the importance of the agriculture good for the households) has a negative impact on the growth performance of the economy (see last column of Table 3.6). This is because less resources are spent in the modern sector, and there are no strong incentives for firms to innovate (profits are low).

Another implication of an increase in α is that employment shares change, with more (less) labor bein employed in the agriculture (modern) sector. Overall, the results shown in Table 3.6 and Figure 3.9 reveal that having a small agriculture sector is good for the growth

α	L_A	L_M	$\frac{L_A}{L_M}$	g
0.025	0.046	0.842	0.055	0.0222
0.050	0.091	0.810	0.113	0.0192
0.075	0.136	0.780	0.174	0.0164
0.100	0.179	0.752	0.239	0.0133
0.125	0.224	0.729	0.307	0.0090

Table 3.6. Employment Shares and Growth performance. Impact of changes in consumption shares (α) on the long–run equilibrium.

prospects of the economy. This is line with the common wisdom that structural change is positively associated with fast growth. At the same time, the comparative statics exercise w.r.t. θ reveals that a small agriculture sector can also be associated to lower growth, if the labor is employed in relatively inefficient technologies in the modern sector. In other words, *ceteris paribus*, changes in the consumption shares in favor of the modern sector are unambiguously associated to faster growth, while the same is not true for changes in the employment shares.

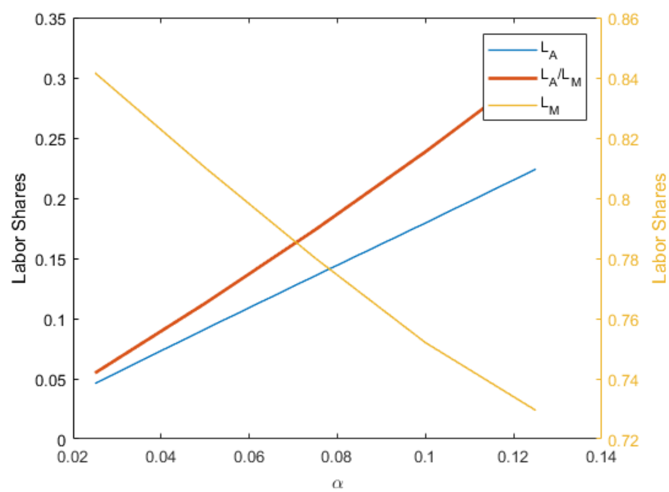

Figure 3.9. Effect of Inequality on Employment Shares, under the baseline calibration.

3.7 Concluding Remarks

We have documented that, contrary to common wisdom, large movements of labor out of agriculture are not always growth–enhancing. In particular, high–inequality economies typically undergo the structural change phenomenon without benefeting much to the extent of growth. Motivated by this evidence, we have developed an endogenous growth model in which the income distribution has implications for the employment shares of the econ-

omy. Income inequality also matters for growth, as different household will demand different goods, which makes markets more or less attractive for innovating firms.
The model is able to replicate the fact that economies characterized by high levels of income inequality grew less in the last decades, even though they faced a similar structural transformation process as other countries.
The entire analysis was based on the analysis of the balanced growth path, with comparative statics exercises. In the future, we plan to introduce an additional layer of income non–homotheticity by allowing for a minimum consumption level of the agriculture good. This would imply that different households have different consumption shares between agriculture and non–agriculture goods, and that these shares change as they grow richer, thus generating structural change in the economy. In the light of the findings of this paper, such an exercise would be very interesting, as it would allow to have two different mechanisms at work (a change in the consumption shares besides the change in firm incentives to innovate). Investigating the properties of the transition to the BGP of such an economy looks like an interesting research avenue.

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Appendix of First Chapter

Appendix A - The Data

Construction of Job Histories

The BHPS is a yearly survey, and therefore its basic structure contains yearly observations for each individual. Among the available variables, individuals report what their employment status and occupation is at the moment of the interview and when the current spell began. In addition to the main dataset, there is a separate annex in which individuals list their detailed job history in the last 12 months. Each single spell is identified with a start date and an end date. When the month of the start date is missing, we replace it with the month of the interview (if the spell began in the same year) or with December (if the spell began in some previous year). In this way, we partly exploit those spells, that otherwise would be completely missing. For each spell we are provided with the employment status, occupation and other information.

We replace the yearly observations by 12 monthly observations for each individual. Then, we fill in the employment status exploiting the information provided. Constructing correctly the job histories is not a straightforward exercise, as the spells reported by individuals sometimes overlap or conflict with each other. In order to solve this issue, we need to set a hierarchical order of the available information. Importantly, we never replace the variables we copy over time once they are assigned, even if they get into conflict with some future source of information. We give priority to the current spell report, as the amount of recall needed to report it correctly is smaller than for past spells. Therefore, first of all we copy the current employment status over time, from the start date of the current spell to the date of the interview. Second, we use past spells to fill in the remaining missing values. Again, we assume that recalls closer in time are more reliable and therefore we first consider the very last spell, then the second last and so on.

We fix 12 as the maximum number of difference in months between the interview (moment of the recall) and the variable to assign (object of the recall). For individuals who are interviewed every year this choice has virtually no effect, as their employment sequences are constructed simply using for each given year the information provided in the interview of the same year. For the others, this choice is meant to limit the amount of measurement error generated by imperfect recall. We noticed that individuals often change their answer to the lenght of the current spell or modify the order or the nature of a job spell, even after years. This implies that without fixing a maximum time difference for assigning the variables, we would end up with a dataset that included pieces of different spell, oftern misreported, one after the other.

Employment Status Imputation of Friends

Individuals are asked about the employment status of their friends once per two years. What is available in the basic structure of the BHPS is therefore a unique observation. Unfortunately we cannot construct the job histories of friends, as no identification number is reported. In order to keep the monthly frequency, we replicate the information on friends over the following 12 months. This is done also to keep relatively large the sample size. Our imputation procedure is based on the assumption that the employment status features a relatively large degree of persistence over time. This is certainly true for employment spell, as the job separation rate in the sample is small and implies long average job duration. It is also true for unemployment spells, as the average unemployment spell duration is above one year. By replicating the employment status in the following 12 months we are simply assuming that those spells of friends are average ones. The only risk we bear is to misplace them in time.

Sector Imputation of Unemployed

The unemployed, by definition, do not belong to any occupational sector. One might even argue that unemployed are simply looking for some job, regardless of any occupational classification. Instead, we believe that we gain useful insights by imputing sector of search to the unemployed. From the data we see that individuals do not change occupational sector often and, even when they do so, the change is usually not dramatic (e.g. movements from sector 2 to sector 3). Moreover, it seems reasonable to think that individuals target their job search to some particular sector of the economy, consistently with their educational level, qualifications and past occupations. Therefore we treat unemployed workers -for which the sector is in principle missing- as if they were still belonging to some occupational sector. Furthermore, for the purpose of our analysis we need to assign them to some sector.
The problem is that we do not really know in which sector they are seeking jobs. The idea behind our imputation is very simple: by logic, the sector where an unemployed worker finds a job is just the sector where he was seeking jobs. The only limitation is that we assign the whole unemployment spell to that particular sector, without allowing for movements across sectors within the spell. When the sector after the unemployment spell is not reported, then we use the previous sector. In any case, to limit the amount of measurement error

generated by our imputation, we only consider spells that immediately follow (or precede) the unemployment spell of interest.

Educational and Occupational Classification

For constructing educational groups, we consider the highest educational qualification achieved by individuals. The original variable contains more than ten possible values, with an elevated degree of details. We collpase those ten groups into four. The first group corresponds to those who hold a Bachelor's degree or some higher degree. The second group includes the individuals with a high school diploma or qualifications for teaching or nursing. Individuals with an A level or O level fall into the third group. Finally, the fourth group is for those who hold no qualification whatsoever.

With respect to the occupational classification, we follow the aggregation in major group of the SOC as proposed by the Employment Department Group and the Office of Population Cansuses and Surveys. The BHPS uses the SOC90 (Standard Occupational Classification), a three-digit code, for describing occupations. At the most disaggregated level we have 347 categories, and in order to analyze the persistence across sectors we need to aggregate them. We choose the aggregation in major groups (9 categories) as the one able to preserve some substantial degree of persistence while keeping a satisfactory level of details.

For further details, refer to "Standard Occupational Classification - Structure and Definition of Major, Minor and Unit Groups, Volume 1"

Representativeness of the BHPS sample

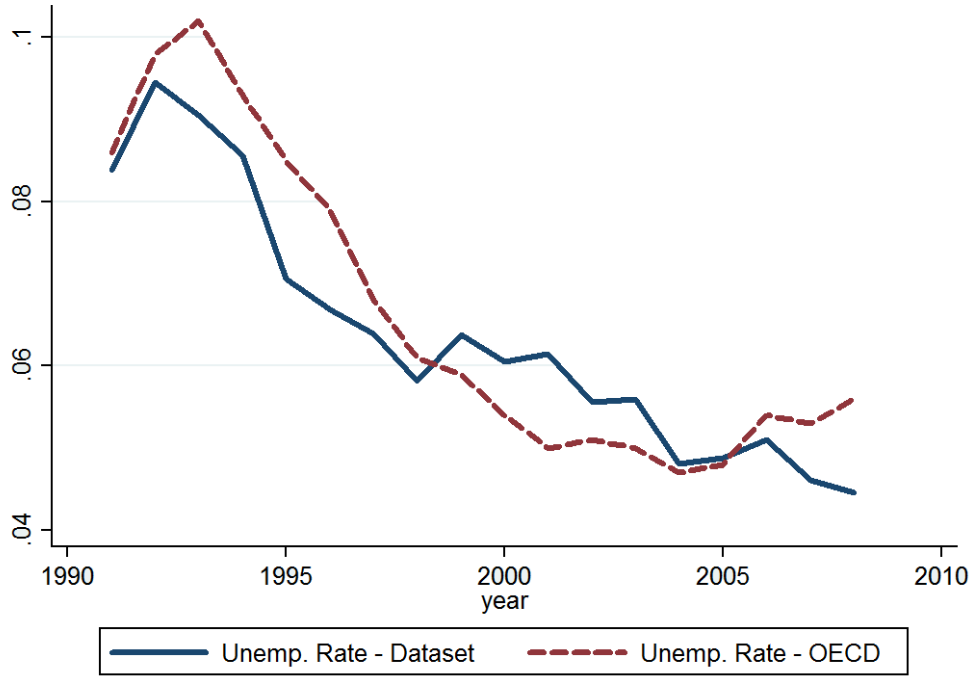

Figure 10. In-sample unemployment rate compared to the Harmonized Unemployment Rate in UK, 1991-2008 (Source: OECD).

Appendix B - Additional Tables

Summary Statistics

Table 7. Summary statistics of labor market outcomes. Source: BHPS (1991-2008).

Variable	Subsample	Mean	N
Unemployment Rate	All Sample	6.15	1685930
	Males	7.24	865469
	Females	5.00	820051
Job Finding Rate	All Sample	7.21	99532
	Males	7.15	60356
	Females	7.32	39121
Job Separation Rate	All Sample	0.42	1549143
	Males	0.49	786531
	Females	0.34	762282

Markov Matrices

Table 8. Markov matrix of occupational mobility: fathers when sons are 14-fathers over their life-cycle, relative frequencies. Source: BHPS (1991-2008)

Father's sector when son is 14	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**59.32**	4.41	6.16	7.32	6.31	1.63	6.33	7.10	1.42
2	16.03	**68.07**	9.13	3.07	0.72	0.33	1.12	0.66	0.86
3	11.72	11.11	**54.46**	10.82	4.28	0.18	4.85	1.01	1.58
4	14.72	2.10	2.60	**49.86**	3.38	8.08	15.22	4.04	0.00
5	5.16	2.54	3.89	1.85	**65.88**	3.19	0.37	12.75	4.37
6	9.54	0.19	18.41	21.96	3.61	**38.66**	1.94	3.51	2.18
7	27.79	0.00	1.59	9.95	4.58	0.00	**33.60**	18.49	4.01
8	8.24	3.47	1.08	1.11	8.91	1.86	1.15	**70.11**	4.07
9	14.81	15.68	0.50	4.16	12.28	5.45	4.18	22.36	**20.59**

Table 9. Markov matrix of occupational mobility: mothers when daughters are 14-mothers over their life-cycle, relative fequencies. Source: BHPS (1991-2008)

Mother's sector when daughter is 14	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**46.01**	0.00	6.78	21.68	0.00	16.29	1.54	6.36	1.33
2	0.98	**62.87**	19.81	7.57	0.00	0.94	0.00	2.29	5.53
3	1.61	7.20	**69.76**	4.66	0.72	10.90	0.76	0.68	3.70
4	17.05	3.21	5.88	**62.81**	0.88	2.11	5.04	0.27	2.75
5	2.25	0.00	3.56	43.34	**12.66**	9.10	16.60	6.94	5.53
6	13.49	2.59	6.14	12.88	0.23	**46.58**	6.44	1.68	9.97
7	7.61	5.80	1.91	12.83	4.92	13.02	**40.40**	0.81	12.70
8	3.02	0.98	13.06	28.24	9.71	3.59	8.00	**28.41**	4.98
9	7.08	4.60	5.21	6.17	0.28	12.29	12.83	3.19	**48.34**

Descriptive Statistics of different groups

Table 10. Descriptive statistics (averages) of different groups: offspring of unemployed fathers, employed fathers and employed fathers in their same occupational group. Source: BHPS (1991-2008).

Variable	**Father unemployed**	**Father Employed**	**Father in Same Sector**
% Female	45	48	32
% Smoker	27	25	30
Age	21.44	22.22	23.49
% College-educated	6	12	13
% Married	6	10	13
% Non-White	7	3	1
Modal Sector	6	4	5

Diff-in-diff: Alternative Definition of Control Group

	Dependent Variable		
	(1) Emp.Status	(2) Job Finding	(3) Job Separation
Father's emp. status (2m, lagged)	0.00415	-0.0254	-0.000894
	(0.025)	(0.037)	(0.003)
Less than 11 yrs. of pot. experience	-0.0563	-0.0876**	0.000791
	(0.038)	(0.043)	(0.003)
Less than 11 yrs. of pot. experience* Father's emp. status (2m, lagged)	0.0770**	0.103***	-0.00102
	(0.036)	(0.038)	(0.003)
N	117110	8160	106833
R^2	0.069	0.041	0.007

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11. Difference-in-differences regressions of Employment Status. The control group is given by individuals with more than 10 years of potential experience in the labor market. We report the coefficient of the **employment status of father**, of **belonging to the treatment group**, the **interaction term** (the effect we want to estimate). Standard errors are clustered at the father level. All regressions include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

Diff-in-diff: Heterogeneity Analysis

	Dependent Variable	
	(1)	(2)
	Emp.Status	Emp.Status
Father's emp. status (2m, lagged)	0.0120	0.0155
	(0.032)	(0.026)
Younger than 27	-0.0834	-0.0613
	(0.051)	(0.040)
Younger than 27*Father's emp. status (2m, lagged)	0.0856*	0.0802**
	(0.051)	(0.039)
Younger than 27*Father's emp. status (2m, lagged)*Female	-0.0307	
	(0.066)	
Younger than 27*Father's emp. status (2m, lagged)*College		-0.105**
		(0.052)
N	120460	120460
R^2	0.068	0.064

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12. Difference-in-differences regressions of Employment Status. The control group is given by individuals aged at least 27. We report the coefficient of the **employment status of father**, of **belonging to the treatment group**, the **treatment effect** and the **treatment effect interacted** with Female in Column 1 and with College in Column 2 (the differential effect we want to estimate). Interactions between Female (or College, respectively) and the Employment Status of Father and the treatment group indicator are also included in the model, altough the coefficients are not reported. Standard errors are clustered at the father level. All regressions include all controls previously discussed.

Diff-in-diff: Regressions for Mother

	Dependent Variable		
	(1)	(2)	(3)
	Emp.Status	Job Finding	Job Separation
Mother's emp. status (2m, lagged)	-0.00894	0.0664***	0.00394*
	(0.027)	(0.024)	(0.002)
Younger than 27	-0.0779**	0.0283	0.00624
	(0.040)	(0.038)	(0.005)
Younger than 27*Mother's emp. status (2m, lagged)	0.0835**	-0.0376	-0.00753
	(0.039)	(0.032)	(0.005)
N	110711	7728	100897
R^2	0.060	0.044	0.006

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13. Difference-in-differences regressions of Employment Status, Job Finding and Job Separation. The control group is given by individuals aged at least 27. We report the coefficient of the **employment status of mother**, of **belonging to the treatment group**, the **interaction term** (the effect we want to estimate). Standard errors are clustered at the mother level. All regressions include all controls previously discussed.

Appendix of Second Chapter

Derivations and Proofs

Empirical Prediction 2

Using the symmetry of the equilibrium, we can write the following:

$$P(\bar{w} = 1|\bar{w}^F = 1) = P(\bar{w} = 1|\bar{w}^F = 1; o^F = A). \tag{34}$$

Next, we define $\bar{w}_j$ as a dummy taking value 1 when the joint event $(\bar{w} = 1; o = j)$ is satisfied (that is, the individual is a high–earner in occupation j). We can now rewrite the previous expression as:

$$P(\bar{w} = 1|\bar{w}_A^F = 1) = P(\bar{w}_A = 1|\bar{w}_A^F = 1) + P(\bar{w}_B = 1|\bar{w}_A^F = 1), \tag{35}$$

using the fact that $\bar{w}_A = 1$ and $\bar{w}_B = 1$ are mutually exclusive events. The first term of Equation (35) can be calculated as follows:

$$\begin{aligned} P(\bar{w}_A = 1|\bar{w}_A^F = 1) &= P(o = A; \tau = A|o^F = A; \tau^F = A) = \\ &= P(o = A|\tau = A; o^F = A; \tau^F = A)P(\tau = A|o^F = A; \tau^F = A) = \rho. \end{aligned} \tag{36}$$

In contrast, the second term of Equation (35) can be rewritten as follows:

$$\begin{aligned} P(\bar{w}_B = 1|\bar{w}_A^F = 1) &= P(o = B; \tau = B|o^F = A; \tau^F = A) = \\ &= P(o = B|\tau = B; o^F = A; \tau^F = A)P(\tau = B|o^F = A; \tau^F = A) \\ &= (1 - \mu)(1 - \rho). \end{aligned} \tag{37}$$

By substituting the last two equations into (35), we arrive at the result.

Lemma 1

Proof. Taking the derivative of m^* w.r.t. μ:

$$\frac{\partial m^*}{\partial \mu} = \frac{-\rho(1 + \mu(1 - 2\rho)) - (1 - \mu\rho)(1 - 2\rho)}{[1 + \mu(1 - 2\rho)]^2}$$

The numerator can be simplified to $(1 + \mu)(\rho - 1)$, which is clearly non–positive, $\forall\ \rho \leq 1$. Therefore, $\frac{\partial m^*}{\partial \mu} \leq 0$.
Taking the derivative of m^* w.r.t. ρ:

$$\frac{\partial m^*}{\partial \rho} = \frac{-\mu(1 + \mu(1 - 2\rho)) - (1 - \mu\rho)(-2\mu)}{[1 + \mu(1 - 2\rho)]^2}$$

The numerator can be simplified to $(1 + \mu)\mu$, which is clearly non–negative, $\forall\ \mu \geq 0$. Therefore, $\frac{\partial m^*}{\partial \rho} \geq 0$. □

Lemma 2

Proof. Taking the derivative of Ψ^* w.r.t. μ:

$$\frac{\partial \Psi^*}{\partial \mu} = \frac{(1 - 2\rho)[1 + \mu(1 - 2\rho) - \rho - \mu + 2\mu\rho]}{[1 + \mu(1 - 2\rho)]^2}$$

The numerator can be simplified to $(1 - 2\rho)(1 - \rho)$, which is clearly non–positive, $\forall\ \rho \geq \frac{1}{2}$. Therefore, $\frac{\partial \Psi^*}{\partial \mu} \leq 0$.

Taking the derivative of Ψ^* w.r.t. ρ:

$$\frac{\partial \Psi^*}{\partial \rho} = \frac{(1-2\mu)[1+\mu(1-2\rho)] + 2\mu[\rho+\mu-2\rho\mu]}{[1+\mu(1-2\rho)]^2}$$

The numerator can be simplified to $1-\mu$, which is clearly non–negative, $\forall\ \mu \leq 1$. Therefore, $\frac{\partial \Psi^*}{\partial \rho} \geq 0$. $\square$

Lemma 3

Proof. Taking the derivative of γ^* w.r.t. μ:

$$\frac{\partial \gamma^*}{\partial \mu} = -\frac{[(1-\Psi^*)(1+N) - \mu(1+N)\frac{\partial \Psi^*}{\partial \mu}U^* - (1-\Psi^*)\mu(1+N)\frac{\partial U^*}{\partial \mu}}{(U^*)^2}$$

The numerator can be rearranged as
$-\left[(1-\Psi)[(1+N)U^* - \mu(1+N)\frac{\partial U^*}{\partial \mu}] - \mu(1+N)\frac{\partial \Psi^*}{\partial \mu}U^*\right]$.
The term $\mu(1+N)\frac{\partial \Psi^*}{\partial \mu}U^*$ is clearly non–positive, since $\frac{\partial \Psi^*}{\partial \mu} \leq 0$. For the first term, it suffices to show that: $U^* \geq \mu\frac{\partial U^*}{\partial \mu}$. The left–hand side of this inequality can be written as $1+\mu N+\Psi(1-\mu)n$, while the right–hand side is: $\mu N + \mu\frac{\partial \Psi^*}{\partial \mu}(1-\mu)n - \mu\Psi n$. Cancelling terms yields: $1+\Psi^* n \geq \mu\frac{\partial \Psi^*}{\partial \mu}(1-\mu)n$, which is always satisfied, since $\frac{\partial \Psi^*}{\partial \mu} \leq 0$. Hence, the whole term in square brackets is non-negative, and therefore $\frac{\partial \gamma^*}{\partial \mu} \leq 0$.
Taking the derivative of γ^* w.r.t. ρ yields:

$$\frac{\partial \gamma^*}{\partial \rho} = -\frac{-\mu(1+N)\frac{\partial \Psi^*}{\partial \rho} - (1-\Psi^*)\mu(1+N)\frac{\partial \Psi^*}{\partial \rho}[(1-\mu)n]}{(U^*)^2}$$

The numerator can be rearranged to: $\frac{\partial \Psi^*}{\partial \rho}[-\mu(1+N) - (1-\Psi^*)\mu(1+N)(1-\mu)n]$. The term in square brackets is non–positive, and the fact that $\frac{\partial \Psi^*}{\partial \rho} \geq 0$ completes the claim that $\frac{\partial \gamma^*}{\partial \rho} \geq 0$. $\square$

Lemma 4

We evaluate the free–entry condition at equilibrium:

$$q(\theta^*)(1-\beta)(1+\gamma^* a) = \kappa$$

The fact that $q'(\theta) < 0$ implies that θ^* adjusts to the new equilibrium in the same direction as γ^*. The fact that $\frac{\partial \gamma^*}{\partial \mu} \leq 0$, $\frac{\partial \gamma^*}{\partial \rho} \geq 0$ (shown in Lemma 3) completes the claim that $\frac{\partial \theta^*}{\partial \mu} \leq 0$ and $\frac{\partial \theta^*}{\partial \rho} \geq 0$.

Proposition 1

We evaluate persistence at equilibrium:

$$\mathcal{P}^* = \mu + (1-\mu)\Psi^*$$

Taking the derivative of $\mathcal{P}^*$ w.r.t. μ:

$$\frac{\partial \mathcal{P}^*}{\partial \mu} = (1-\mu)\frac{\partial \Psi^*}{\partial \mu} + (1-\Psi^*)$$

The first term is negative, while the second is always positive. We can show that even in the case of $\mu = 0$ (that is, making the negative term as large as possible), the sum of the two is still positive. To see this, we use some of the expressions derived earlier:

$$(1-\Psi^*) = \frac{1-\rho}{[1+\mu(1-2\rho)]} \geq -\frac{(1-2\rho)(1-\rho)}{[1+\mu(1-2\rho)]^2} = -\frac{\partial \Psi^*}{\partial \mu},$$

where the inequality follows from the fact that $1 \geq -(1-2\rho)(1-\mu)$. Hence, $\frac{\partial \mathcal{P}^*}{\partial \mu} \geq 0$. We now take the derivative of $\mathcal{P}^*$ w.r.t. ρ:

$$\frac{\partial \mathcal{P}^*}{\partial \rho} = (1-\mu)\frac{\partial \Psi^*}{\partial \rho},$$

which is clearly positive, given that $\frac{\partial \Psi^*}{\partial \rho} \geq 0$.

Definition of different subgroups of workers

Subgroup #	Father Well–sorted	Same τ as father	Large Network	Share
1	Yes	Yes	Yes	$m\rho\mu$
2	Yes	Yes	No	$m\rho(1-\mu)$
3	Yes	No	Yes	$m(1-\rho)\mu$
4	Yes	No	No	$m(1-\rho)(1-\mu)$
5	No	Yes	Yes	$(1-m)\rho\mu$
6	No	Yes	No	$(1-m)\rho(1-\mu)$
7	No	No	Yes	$(1-m)(1-\rho)\mu$
8	No	No	No	$(1-m)(1-\rho)(1-\mu)$

Table 14. Description of the different subgroups of workers.

Expression for m and $\mathcal{P}$

$$m(m_1, ..., m_8) = \frac{\rho\mu m_5 + \rho(1-\mu)m_6 + (1-\rho)\mu m_7 + (1-\rho)(1-\mu)m_8}{1+\rho\mu(m_5-m_1)+\rho(1-\mu)(m_6-m_2)+(1-\rho)\mu(m_7-m_3)+(1-\rho)(1-\mu)(m_8-m_4)}.$$

$$\mathcal{P}(m, m_1, ..., m_8) = m\Big[\rho(\mu m_1 + (1-\mu)m_2) + (1-\rho)(\mu(1-m_3) + (1-\mu)(1-m_4))\Big] \\ + (1-m)[\rho(\mu(1-m_5) + (1-\mu)(1-m_6)) + (1-\rho)(\mu m_7 + (1-\mu)m_8)\Big]. \tag{38}$$

$$\frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m}\frac{\partial m}{\partial m_j}\Big|_{\vec{m}^{SE}} = \Big[[p(\theta)y(1+a) - \kappa\theta](2\rho-1)(1-\mu)n + p(\theta)ya(2\rho-1)\mu(1+N)\Big]\frac{\partial m}{\partial m_j}\Big|_{\vec{m}^{SE}} > 0. \tag{39}$$

Proposition 2: *Depending on the parameter values, the SE allocation $\vec{m}^{SE}$ does not necessarily coincide with the efficient one.*

- *Under $a > \frac{N}{1+N} - \frac{N}{1+N}\frac{\kappa\theta}{p(\theta)y}$ (Condition a/N^*_+) and $a > \frac{n}{1-n} - \frac{n}{1-n}\frac{\kappa\theta}{p(\theta)y}$ (Condition a/n^{**}_+): $m_3^{*,SP}, m_5^{*,SP} > 0$; $m_4^{*,SP} = m_6^{*,SP} = 1$.*
  That is, the SP wants to achieve less mismatch than in the SE.
- *Under $a < \frac{N}{1+N} - \frac{N}{1+N}\frac{\kappa\theta}{p(\theta)y}$ (Condition a/N^*_-) and $a < \frac{n}{1-n} - \frac{n}{1-n}\frac{\kappa\theta}{p(\theta)y}$ (Condition a/n^{**}_-), $\exists\bar{\rho} > \frac{1}{2}$ such that $\forall\rho < \bar{\rho}$: $m_3^{*,SP} = m_5^{*,SP} = 0$; $m_4^{*,SP}, m_6^{*,SP} < 1$.*
  That is, the SP wants to achieve more mismatch than in the SE.

Proof. First notice that, under $\vec{m}^{SE} = \{1,1,0,1,0,1,1,1\}$, the *reallocation effect* is always strictly positive:

$$\frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m}\frac{\partial m}{\partial m_j}\Big|_{\vec{m}^{SE}} = \Big[[p(\theta)y(1+a) - \kappa\theta](2\rho-1)(1-\mu)n + p(\theta)ya(2\rho-1)\mu(1+N)\Big]\frac{\partial m}{\partial m_j}\Big|_{\vec{m}^{SE}} > 0. \tag{40}$$

Intuitively, the strength of this effect depends on the size of ρ. The larger ρ is, the more scope the SP has to sort workers according to productivity, so that fewer workers have a tradeoff in the next period. It can be seen that as $\rho \to \frac{1}{2}$, $\frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m}\frac{\partial m}{\partial m_j}\Big|_{\vec{m}^{SE}} \to 0$. When productive types are nearly independent across generations, the SP can align productive advantage and networks to a very limited extent (in the limit, he cannot do so at all).

Inspection of the *inner effect*, evaluated at the SE allocation, reveals that $\frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_1}, \frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_2}, \frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_7}, \frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_8} > 0$. This implies that $m_1^{*,SP} = m_2^{*,SP} = m_7^{*,SP} = m_8^{*,SP} = 1$. It remains to find the optimal values of m_3,m_4, m_5 and m_6.

It is important to remember that under the SE allocation, the *reallocation effect (RE)* is positive.
The first statement of Proposition 2 follows from the fact that $\frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_3}\Big|_{\vec{m}^{SE}}, \frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_5}\Big|_{\vec{m}^{SE}} > 0$ under Condition (a/N^*_+), along with $\frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_4}\Big|_{\vec{m}^{SE}}, \frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_6}\Big|_{\vec{m}^{SE}} > 0$ under Condition (a/n^{**}_+).
The second statement of Proposition 2 follows from the fact that $\frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_3}\Big|_{\vec{m}^{SE}}, \frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_5}\Big|_{\vec{m}^{SE}} < 0$ under Condition (a/N^*_-), along with $\frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_4}\Big|_{\vec{m}^{SE}}, \frac{\partial \mathcal{W}^{\mathcal{SP}}}{\partial m_6}\Big|_{\vec{m}^{SE}} < 0$ under Condition (a/n^{**}_-) and the fact that the $RE \to 0$ as $\rho \to \frac{1}{2}$.
Note that these are only sufficient conditions. Given that the RE is positive, there will be additional regions of the parameter space in which the statements are true. □

Proposition 3

We focus on equilibria in which $\eta_V(\theta) \geq (1-\beta)$, so that the indirect effect (GE effect) of an increase in μ (ρ) is negative (positive). We provide a sufficient condition for the direct effect of an increase in μ (ρ) to also be negative (positive). The direct effect of μ is given by:

$$\frac{\partial \mathcal{W}}{\partial \mu} = 2\left[p(\theta)(1+\gamma a)y - \kappa\theta\right]\frac{\partial U}{\partial \mu} + 2p(\theta)ayU\frac{\partial \gamma}{\partial \mu}$$

Replacing $\frac{\partial \gamma}{\partial \mu}$ with the expression found in Lemma 3 and regrouping terms yields:

$$\left[U^2(1+\gamma a)\beta + a(1-\Psi)\mu(1+N)\right]\frac{\partial U}{\partial \mu} \leq a\left[(1-\Psi)(1+N) - \mu(1+N)\frac{\partial \Psi}{\partial \mu}\right]$$

Replacing $\frac{\partial U}{\partial \mu} = N + \frac{\partial \Psi}{\partial \mu}(1-\mu)n - \Psi n$ and defining $A \equiv [U^2(1+\gamma a)\beta + a(1-\Psi)\mu(1+N)]$, we get:

$$-a(1-\Psi)(1+N) \leq -a\mu(1+N)\frac{\partial \Psi}{\partial \mu} - A\left[(1-\mu)n\frac{\partial \Psi}{\partial \mu} + (\Psi n - N)\right]$$

It can easily be verified that $(1-\mu)n\frac{\partial \Psi}{\partial \mu} \leq N - \Psi n$ if the following condition is satisfied:

$$\frac{N}{n} \leq \frac{(1-2\rho)(1-\rho)(1-\mu)n}{[1+\mu(1-2\rho)]^2} + \frac{\rho+\mu-2\rho\mu}{[1+\mu(1-2\rho)]}$$

Hence, $\frac{d\mathcal{W}}{d\mu} \leq 0$.
In the text we have already shown that $\frac{\partial \mathcal{W}}{\partial \rho}$ has to be non–negative. As a consequence, $\frac{d\mathcal{W}}{d\rho} \geq 0$, since it is the sum of two positive components.

Worker Flows

The evolution of the stock of unemployed and employed workers is the result of optimal relocation decisions, age shocks and labor market shocks (creation of new matches and destruction of existing ones). Define $g^k_{\Omega}(\tilde{\Omega}) = P(\Omega' = \Omega|\tilde{\Omega})$ to be the probability measure that a worker of type $\tilde{\Omega}$ with employment status k changes to type Ω in the following period. This probability is defined over the multidimensional distribution of Ω. In particular, it involves changes in: the temporary preference vectors (his own or his father's), occupation–specific human capital and networks stocks (his own or his father's), father's occupation or employment status.

Define $u'_{o,F}(\Omega)$ to be the subsequent period's measure of unemployed fathers of type Ω in occupation o:

$$
\begin{aligned}
u'_{o,F}(\Omega) = & \int_{\Omega} \Big[\hat{u}_{o,F}(\tilde{\Omega})\,(1 - R^U_{o,F}(\tilde{\Omega}))\,(1 - p_{o,F}(\tilde{\Omega}))\,g^U_{\Omega}(\tilde{\Omega}) \\
& + \hat{e}_{o,F}(\tilde{\Omega})\,(1 - R^E_{o,F}(\tilde{\Omega}))\,\delta\,g^E_{\Omega}(\tilde{\Omega}) \Big]\,d\tilde{\Omega} \\
& + \sum_{\tilde{o} \neq o} \int_{\Omega} \Big[\hat{u}_{\tilde{o},F}(\tilde{\Omega})\,R^U_{\tilde{o},F}(\tilde{\Omega}) + \hat{e}_{\tilde{o},F}(\tilde{\Omega})\,R^E_{\tilde{o},F}(\tilde{\Omega}) \Big] \\
& \cdot \mathbb{1}\{j^*_F(\tilde{\Omega}) = o\}\,(1 - p_{o,F}(\tilde{\Omega}))\,g^U_{\Omega}(\tilde{\Omega})\,d\tilde{\Omega},
\end{aligned}
\tag{41}
$$

where $\hat{u}_{o,F} = u_{o,F}\,(1-\zeta) + u_{o,S}\,\zeta$, and $\hat{e}_{o,F} = e_{o,F}\,(1-\zeta) + e_{o,S}\,\zeta$. These are the measures of workers after the age shock, that is they include fathers who did not die, as well as sons who became fathers.

Equation (41) is composed of four different terms: the first two refer respectively to unemployed workers in occupation o who decided not to relocate and did not find a job, and employed workers in occupation o who did not relocate and lost their job; the last two are (unemployed and employed) workers who decided to relocate into occupation o but did not find a job in the previous period.

For employed fathers, $e'_o(\Omega)$ is defined as:

$$
\begin{aligned}
e'_{o,F}(\Omega) = & \int_{\Omega} \Big[\hat{e}_{o,F}(\tilde{\Omega})\,(1 - R^E_{o,F}(\tilde{\Omega}))\,(1-\delta)\,g^E_{\Omega}(\tilde{\Omega}) \\
& + \hat{u}_{o,F}(\tilde{\Omega})\,(1 - R^U_{o,F}(\tilde{\Omega}))\,p_{o,F}(\tilde{\Omega})\,g^U_{\Omega}(\tilde{\Omega}) \Big]\,d\tilde{\Omega} \\
& + \sum_{\tilde{o} \neq o} \int_{\Omega} \Big[\hat{u}_{\tilde{o},F}(\tilde{\Omega})\,R^U_{\tilde{o},F}(\tilde{\Omega}) + \hat{e}_{\tilde{o},F}(\tilde{\Omega})\,R^E_{\tilde{o},F}(\tilde{\Omega}) \Big] \\
& \cdot \mathbb{1}\{j^*_F(\tilde{\Omega}) = o\}\,p_{o,F}(\tilde{\Omega})\,g^U_{\Omega}(\tilde{\Omega})\,d\tilde{\Omega}.
\end{aligned}
\tag{42}
$$

The stock of employed is made up of workers who were already employed in the previous period in the same occupation and did not lose their job nor did they find it profitable to relocate, and the mass of unemployed workers who did not want to relocate and found a vacancy, plus all workers who had just relocated into occupation o and found a job.

The distribution of employed sons, is exactly symmetric to that of the fathers:

$$\begin{aligned}
e'_{o,S}(\Omega) = \int_{\Omega} \Big[& (1-\zeta) e_{o,S}(\tilde{\Omega})\,(1 - R^{E}_{o,S}(\tilde{\Omega}))\,(1-\delta)\, g^{E}_{\Omega}(\tilde{\Omega}) \\
& + (1-\zeta) u_{o,S}(\tilde{\Omega})\,(1 - R^{U}_{o,S}(\tilde{\Omega}))\, p_{o,S}(\tilde{\Omega})\, g^{U}_{\Omega}(\tilde{\Omega}) \Big]\, d\tilde{\Omega} \\
& + \sum_{\tilde{o} \neq o} \int_{\Omega} \Big[(1-\zeta) u_{\tilde{o},S}(\tilde{\Omega})\, R^{U}_{\tilde{o},S}(\tilde{\Omega}) \; + (1-\zeta) e_{\tilde{o},S}(\tilde{\Omega})\, R^{E}_{\tilde{o},S}(\tilde{\Omega}) \Big] \\
& \cdot \mathbb{1}\{ j^{*}_{S}(\tilde{\Omega}) = o \}\, p_{o,S}(\tilde{\Omega})\, g^{U}_{\Omega}(\tilde{\Omega})\, d\tilde{\Omega}.
\end{aligned} \tag{43}$$

Finally, the distribution of unemployed sons is as follows:

$$\begin{aligned}
u'_{o,S}(\Omega) = \int_{\Omega} \Big[& (1-\zeta) u_{o,S}(\tilde{\Omega})\,(1 - R^{U}_{o,S}(\tilde{\Omega}))\,(1 - p_{o,S}(\tilde{\Omega}))\, g^{U}_{\Omega}(\tilde{\Omega}) \\
& + (1-\zeta) e_{o,S}(\tilde{\Omega})\,(1 - R^{E}_{o,S}(\tilde{\Omega}))\, \delta\, g^{E}_{\Omega}(\tilde{\Omega}) \Big]\, d\tilde{\Omega} \\
& + \sum_{\tilde{o} \neq o} \int_{\Omega} \Big[(1-\zeta) u_{\tilde{o},S}(\tilde{\Omega})\, R^{U}_{\tilde{o},S}(\tilde{\Omega}) \; + (1-\zeta) e_{\tilde{o},S}(\tilde{\Omega})\, R^{E}_{\tilde{o},S}(\tilde{\Omega}) \Big] \\
& \cdot \mathbb{1}\{ j^{*}_{S}(\tilde{\Omega}) = o \}\,(1 - p_{o,S}(\tilde{\Omega}))\, g^{U}_{\Omega}(\tilde{\Omega})\, d\tilde{\Omega} \\
& + \zeta\, \frac{\mathbb{1}\{\Omega \in \Omega^{NB}\}}{\int_{\Omega} \mathbb{1}\{\Omega \in \Omega^{NB}\}},
\end{aligned} \tag{44}$$

with the only difference being the last term, which represents the flow of newborns, randomly directed to the subset Ω^{NB} of the entire state space.

Other Figures and Tables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Son is in:	Occ. 1	Occ. 2	Occ. 3	Occ. 4	Occ. 5	Occ. 6	Occ. 7	Occ. 8	Occ. 9
Father is in:									
Occ. 1	0.0335^{***}								
	(0.003)								
Occ. 2		0.0365^{***}							
		(0.003)							
Occ. 3			0.0550^{***}						
			(0.005)						
Occ. 4				0.0411^{***}					
				(0.005)					
Occ. 5					0.151^{***}				
					(0.004)				
Occ. 6						0.0398^{***}			
						(0.005)			
Occ. 7							0.0159^{***}		
							(0.006)		
Occ. 8								0.127^{***}	
								(0.003)	
Occ. 9									0.105^{***}
									(0.006)
N	62114	62114	62114	62114	62114	62114	62114	62114	62114
R^2	0.073	0.196	0.079	0.047	0.106	0.053	0.076	0.084	0.089

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15. Regressions of Occupational Choice (dummy that takes a value of 1 if the offspring is in a given occupation, 0 otherwise); coefficient for **father in a given occupation (dummy variable, 0 if the father is in some other occupation)**, standard errors. All models are linear probability models, and include a third-degree polynomial in age and dummies for education, region of residence, smoking behavior, marital status, ethnicity and quarter. Occupational codes are as defined in Table 2.1: 1) Managers & Administrators; 2) Professional; 3) Associate Professional; 4) Clerical & Secretarial; 5) Craft & Related; 6) Personal & Protective Service; 7) Sales; 8) Plant & Machine; 9) Agriculture & Elementary. Source: BHPS (1991–2008).

Occ. code	Occupational group	Likelihood Ratio	Occ. Share
11	Production Managers in Manuf., Construction	6.23	0.0133
12	Specialist Managers	2.03	0.0210
13	Office Managers	0.00	0.0129
14	Managers in Transport and Storing	4.69	0.0084
16	Managers in Farming	33.05	0.0084
17	Managers in Service Industry	1.92	0.0301
19	Managers and Administrators NEC	3.04	0.0083
21	Engineers and Technologists	4.79	0.0144
22	Health Professionals	0.00	0.0064
23	Teaching Professionals	1.67	0.0112
25	Business and Financial Professionals	12.19	0.0102
31	Draughtspersons	1.77	0.0109
32	Computer Analyst/Programmers	0.00	0.0301
34	Health Associate Professionals	10.66	0.0066
36	Business and Financial Associate Professionals	6.23	0.0186
37	Social Welfare Associate Professionals	0.00	0.0051
38	Literary, Artistic and Sports Professionals	3.01	0.0264
39	Associate Professionals and Technical Occ.s NEC	2.52	0.0056
40	Administrative/Clerical Officers	2.71	0.0088
41	Numerical Clerks and Cashiers	0.00	0.0380
42	Filing and Record Clerks	2.05	0.0188
43	Clerks	0.82	0.0285
44	Stores and Despatch Clerks	3.16	0.0276
50	Construction Trades	5.81	0.0424
51	Metal Machining	1.64	0.0363
52	Electrical/Electronic Trades	6.43	0.0541
53	Metal Forming, Welding and Related	2.57	0.0360
54	Vehicle Traders	5.78	0.0317
57	Woodworking Trades	7.81	0.0322
58	Food Preparation Trades	29.71	0.0103
59	Other Craft and Related Occupations NEC	0.50	0.0185
61	Security and Protective Service	5.08	0.0059
62	Catering Occupations	3.20	0.0268
71	Sales Representatives	1.72	0.0166
72	Sales Assistants and Check-out Operators	0.28	0.0534
80	Food, Drink and Tobacco Process Operatives	35.81	0.0086
82	Chemicals, Paper, Plastics Operatives	5.42	0.0120
84	Metal Working Process Operatives	3.82	0.0088
85	Assemblers/Lineworkers	5.16	0.0132
86	Other Routine Process Operatives	3.51	0.0148
87	Road Transport Operatives	4.54	0.0320
88	Other Transport and Machinery Operatives	7.25	0.0055
89	Plant and Machine Operatives NEC	4.09	0.0138
90	Other Occ.s in Agriculture, Forestry and Fishing	16.96	0.0108
92	Other Occ.s in Construction	11.78	0.0096
94	Other Occ.s in Communication	0.42	0.0080
95	Other Occ.s in Sales and Services	9.22	0.0336
99	Other Occ.s NEC	0.45	0.0120
	Average (unweighted)	5.69	
	Average (weighted)	4.71	

Table 16. Occupational Persistence (Likelihood Ratios), 2–digit level. The table presents the likelihood ratios for occupations in which at least 0.5% of the workforce are employed, due to the limited size of the sample. Averages are taken with respect to all occupations, including the ones not reported in the table. Source: BHPS (1991–2008).

Occupational sector	Likelihood Ratio		
	Bottom 33%	Mid 33%	Top 33%
Managers & Administrators	1.49	0.82	1.51
Professional	2.93	2.61	2.35
Associate Professional & Technical	1.40	1.84	1.60
Clerical & Secretarial	1.43	1.45	1.01
Craft & Related	1.64	1.57	1.46
Personal & Protective Service	1.81	2.72	0.50
Sales	0.99	1.56	1.47
Plant & Machine	2.49	1.48	1.88
Agriculture & Elementary	3.02	2.31	2.72
Average (unweighted)	1.91	1.82	1.61
Average (weighted)	1.79	1.63	1.65

Table 17. Occupational Persistence Indexes, by Father's Income (Likelihood Ratios). Source: BHPS (1991–2008).

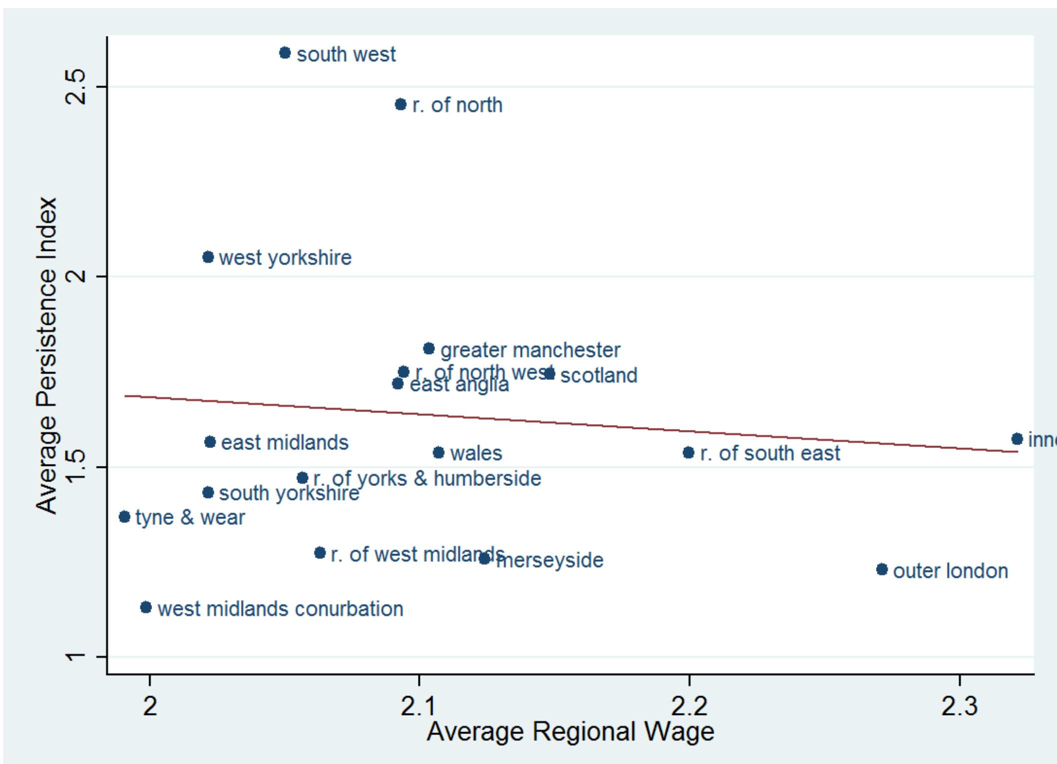

Figure 11. Plot of Average Persistence Index (weighted average of occupation–specific likelihood ratios, by region) vs. Average Regional Wage. Source: BHPS (1991–2008).

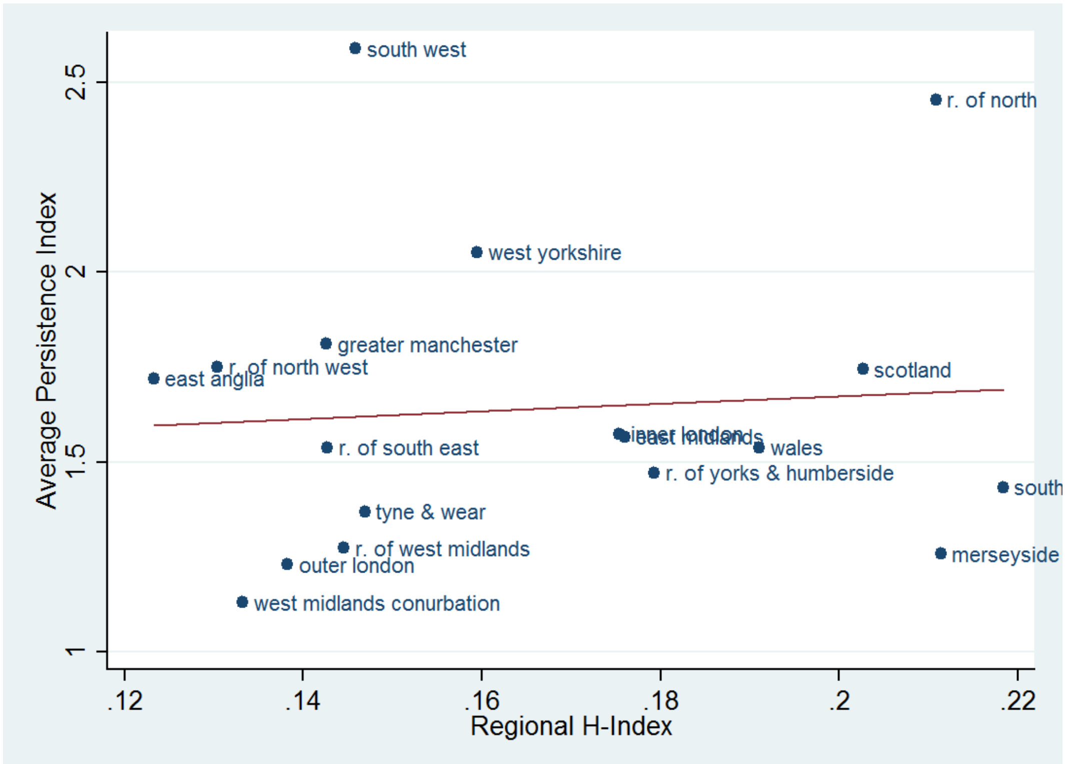

Figure 12. Plot of Average Persistence Index (weighted average of occupation–specific likelihood ratios, by region) vs. Herfindahl index of occupations (at the 1–digit level) . Source: BHPS (1991–2008).

Occupational sector	**Likelihood Ratio**			
(contemporaneous)	**<20**	**20-25**	**25-30**	**30+**
Managers & Administrators	1.78	1.46	1.28	1.20
Professional	3.83	2.36	2.62	2.33
Associate Professional & Technical	2.05	0.91	1.86	2.27
Clerical & Secretarial	1.50	0.73	1.15	2.23
Craft & Related	1.32	1.48	1.73	1.68
Personal & Protective Service	1.19	1.53	2.69	0.61
Sales	1.55	1.45	0.98	1.49
Plant & Machine	1.27	2.07	2.06	1.89
Agriculture & Elementary	2.48	2.31	2.86	4.51
Average (unweighted)	1.88	1.59	1.91	2.03
Average (weighted)	1.62	1.49	1.83	1.92

Table 18. Occupational Persistence Indexes, by Son's Age Group (Likelihood Ratios). Source: BHPS (1991–2008).

Dependent Variable: Job–Finding Rate

	(1) POLS	(2) RE	(3) FE
Panel A			
Father in same occupation ($\pi_{i,t}$)	0.0481***	0.0497**	0.0564**
	(0.016)	(0.020)	(0.025)
Average in–sample JF	0.125	0.125	0.125
N	4098	4098	4098
R^2	0.055	-	0.047
Number of pairs	-	400	400
Panel B			
Father in same occupation ($\pi_{i,t}$)	0.0821***	0.0793**	0.0882**
	(0.025)	(0.032)	(0.039)
Average in–sample JF	0.115	0.115	0.115
N	2093	2093	2093
R^2	0.084	-	0.074
Number of pairs	-	212	212

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 19. Robustness Checks: Regressions of job–finding rate (transition from Unemployed to Employed); coefficient for **father in same occupation** (dummy variable), standard errors and average job–finding rate in the regression sample. Model 1 is a pooled OLS regression, model 2 is a random effects GLS regression, and model 3 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behavior, marital status, ethnicity, quarter and occupation of search/employment. In Panel A, we exclude the spells of self–employment from the estimation. In Panel B, we exclude all the workers who report having been self–employed at least once in their lifetime. Source: BHPS (1991–2008).

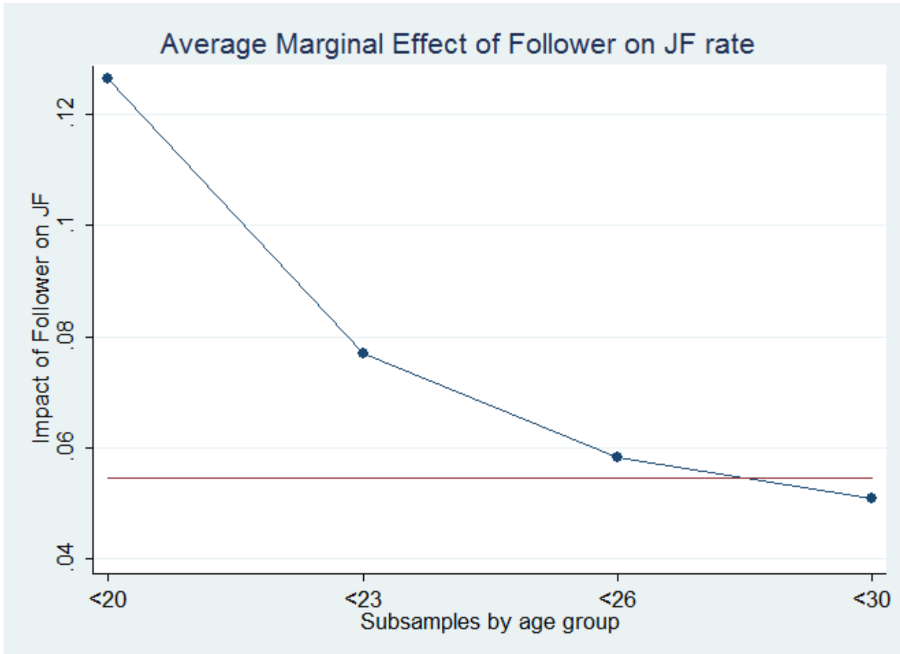

Figure 13. Average marginal effect of $\pi_{i,t}$ (coefficient of Column 1 of Table 2.3), by age group. The red line is the average marginal effect for the entire sample. Source: BHPS (1991–2008).

Dependent Variable: Job–Finding Rate

	(1)	(2)
Father in same occupation ($\pi_{i,t}$)	0.0404**	0.0437**
	(0.018)	(0.018)
Father with high tenure (dummy: 1 if above average) ($ht_{i,t}$)	-0.0266*	
	(0.014)	
Interaction term ($\pi^*_{i,t}ht_{i,t}$)	0.0634	
	(0.039)	
Log of father's tenure in years ($\log(t_{i,t})$)		-0.00512
		(0.006)
Interaction term ($\pi^*_{i,t}\log(t_{i,t})$)		0.0207
		(0.014)
N	4142	3726
R^2	0.059	0.062

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20. Robustness Checks: Regressions of job–finding rate (transition from Unemployed to Employed); coefficient for **father in same occupation** (dummy variable), **father with high tenure** (dummy variable), **father's occ. tenure** (log), **interaction terms** and standard errors. Both models are pooled OLS regressions. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behavior, marital status, ethnicity, quarter and occupation of search/employment. Source: BHPS (1991–2008).

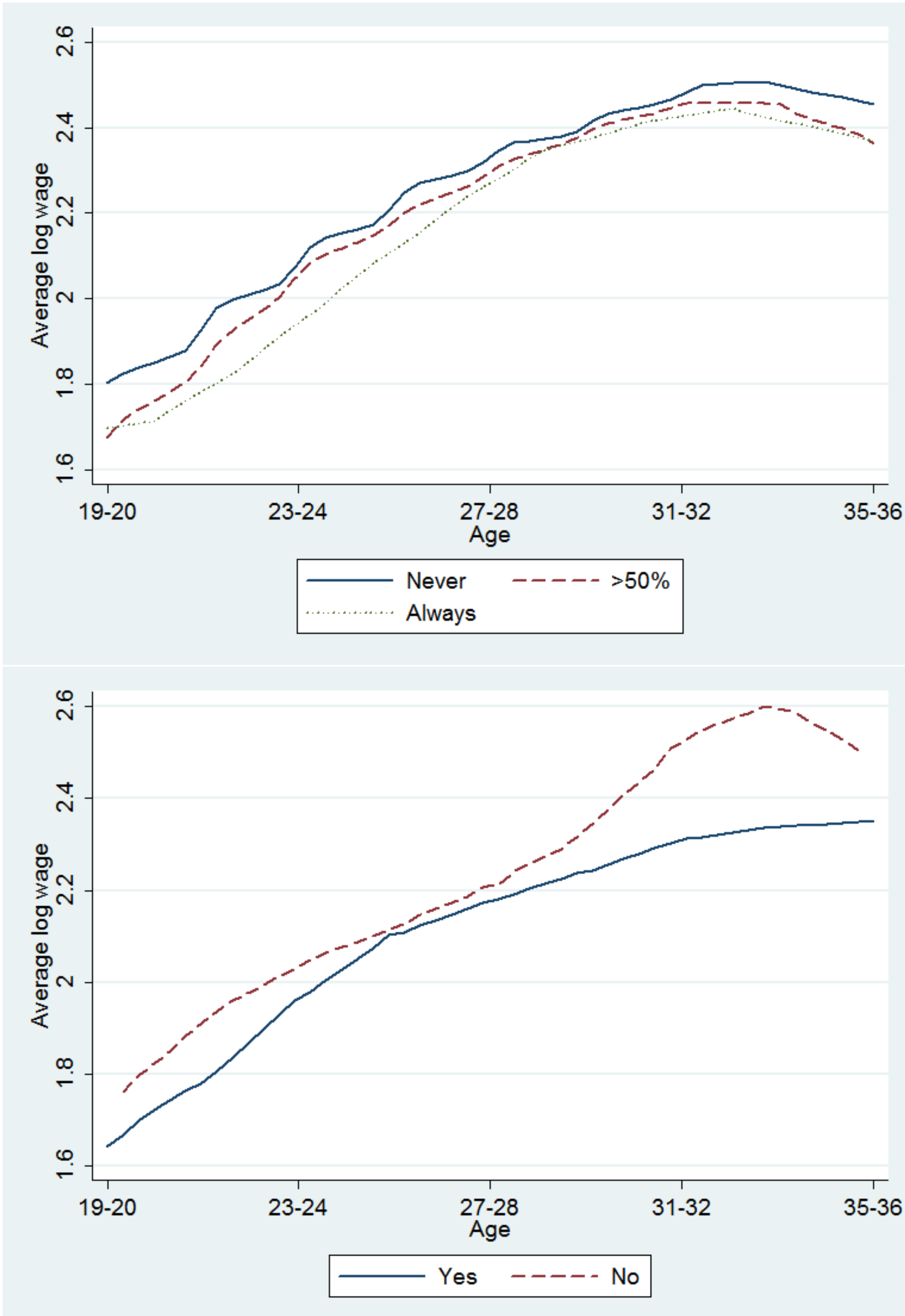

Figure 14. Wage profiles by proportion of job spell with the father in the same occupation. In the upper graph, groups are defined with respect to the entire job spell length. In the lower graph, groups are defined with respect to the start of the job spell. Source: BHPS (1991–2008).

Dependent Variable: Log Hourly Wage

	(1) POLS	(2) RE	(3) POLS	(4) RE	(5) FE
Panel A					
Share of time in occ. of father (q_i)	-0.134***	-0.155***			
	(0.016)	(0.031)			
Father in same occupation ($\pi_{i,t}$)			-0.073***	-0.032**	-0.007
			(0.013)	(0.013)	(0.014)
N	6324	6324	4664	4664	4664
R^2	0.617	-	0.602	-	0.639
Number of pairs	-	908	-	833	833
Panel B					
Share of time in occ. of father (q_i)	-0.0967***	-0.109***			
	(0.015)	(0.029)			
Father in same occupation ($\pi_{i,t}$)			-0.050***	-0.019	-0.003
			(0.012)	(0.012)	(0.012)
N	5664	5664	4159	4159	4159
R^2	0.547	-	0.540	-	0.606
Number of pairs	-	866	-	788	788

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21. Robustness Checks: Regressions of Log Hourly Wage; coefficient for **share of time spent in same occupation as father** (from 0 to 1), standard errors and **father in same occupation** (dummy variable). Models 1 and 3 are pooled OLS regressions, models 2 and 4 are random effects GLS regressions, and model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education and occupation, second–order polynomials in occupational tenure and potential labor market experience, firm size, region of residence, smoking behavior, marital status, ethnicity and year. Panel A excludes from the estimating sample all wage observations above percentile 99 or below percentile 1. Panel B excludes from the estimating sample all wage observations above percentile 95 or below percentile 5. Source: BHPS (1991–2008).

Dependent Variable: Occupational Persistence Rate

	(1)	(2)
Father's log wage	0.0419***	0.0481***
	(0.016)	(0.016)
Log wage		-0.0779***
		(0.017)
Avrage in–sample Persistence Rate	0.172	0.172
N	3467	3467
R^2	0.134	0.139

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22. Regressions of Occupational Persistence (being in the same occupation as the father); coefficient of **father's log wage** and **log wage**, standard errors and average job–finding rate in the regression sample. Both models are pooled OLS regressions. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behavior, marital status, ethnicity, quarter, and occupation of search/employment. Source: BHPS (1991–2008).

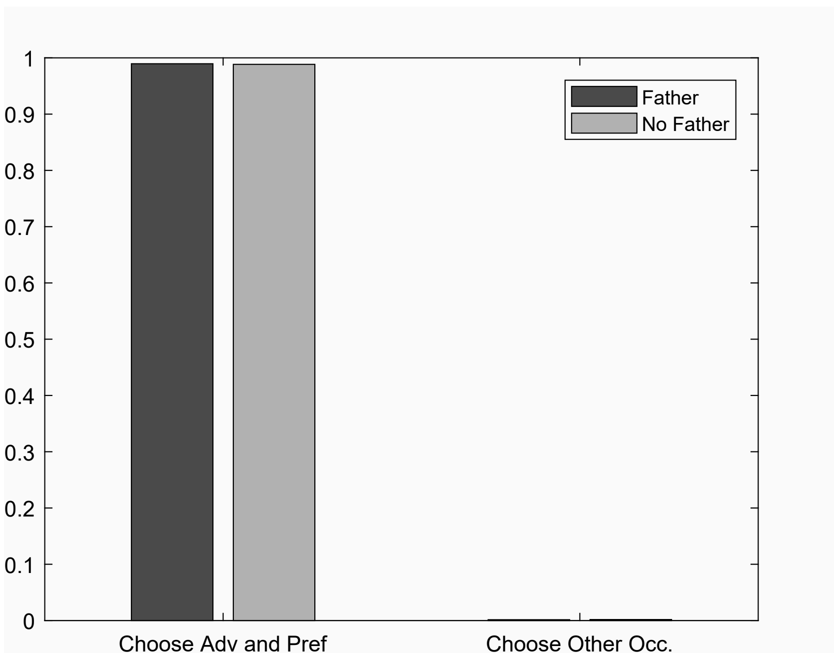

Figure 15. Plot of Average Policy Function (Occupational Choice), for unemployed workers with comparative advantage and preference in the same occupation as the father. Source: BHPS (1991–2008).

Parameter	Description	Value	Target/Source	Data	Model
Intergenerational Transmission					
ξ	Transmission of Networks	0*	JF premium of followers (BHPS)	[0.055]	0.001
ρ_τ	Transmission of Comparative Advantage	1.000	Difference in Proportion of Followers by Father's wage (BHPS)	0.023	0.256
ρ_ϕ	Transmission of Preferences	0.111*	Interg. Occupational Persistence (Lik. Ratio, BHPS)	1.720	1.597
Heterogeneity and Laws of Motions					
$\hat{h}$	HC premium	0.260	Average occupational tenure returns after 5 years (BHPS)	-	-
$\hat{n}$	Networks premium	1.700	Proportion of jobs found through contacts (Pellizzari 2010b)	0.230	0.229
$\hat{\tau}$	Comparative Advantage premium	1.042	Within–occupation log wage variance (BHPS)	0.166	0.181
$\bar{\phi}$	Baseline preference for jobs	0	Normalization	-	-
$\hat{\phi}$	Preference premium	0.882	Wage discount of followers (BHPS)	[0.076]	-0.316
p_h^+	Probability of accumulating HC (employed)	0.0166	Average occupational tenure returns after 5 years (BHPS)	0.260	0.260
p_h^-	Probability of losing HC (unemployed)	0.390	Average wage discount after unemp. (Arulampalam 2001)	0.076	0.072
p_n^+	Probability of accumulating networks (employed)	0.003	Regression of JF rate vs. past occupational tenure (BHPS)	0.008	0.008
p_n^-	Probability of losing networks (unemployed)	0.117	JF rate–unemployment duration profile (see text, BHPS)	1.066	1.094
σ	Standard deviation of preference shocks	0.348	Occupational change rate, after U spell (monthly, BHPS)	0.357	0.365
Environment					
O	Number of occupations	9	1-digit SOC aggregation	-	-
κ	Vacancy posting cost	4.765	Average UE rate (monthly, BHPS)	0.125	0.112
δ	Exogenous separation rate	0.003	Average EU rate (monthly, BHPS)	0.005	0.005
λ	Discount factor	0.9966	From literature	-	-
ζ	Age shock	0.00416	Average length of worklife: 20 (young) + 20 (old) years	40	40
b	Unemployment benefit	0.584	Average replacement rate (OECD)	0.530	0.509
χ	Surplus sharing rule	0.7	Normalization	-	-
A	TFP parameter of matching function	0.1	Normalization	-	-
γ	Elasticity of matching function w.r.t. unemp.	0.5	Normalization	-	-

Table 23. Calibration Results, Restricted Model (* = restricted parameters; [] = non-targeted moments)

Appendix of Third Chapter

Appendix A - The Data

Penn World Tables 7.1: this data is collected by the Center for International Comparisons at the University of Pennsylvania (CICUP). It provides PPP and national income accounts converted to international prices for 189 countries for some of (or all) the years between 1950 and 2010.
GGDC 10–Sector Database: it is collected by the Growth and Development Center of the University of Groningen. It provides a long–run internationally comparable series of persons employed and productivity performance for 10 broad sectors of the economy (Agriculture, Mining, Manufacturing, Utilities, Construction, Trade Services, Transport Services, Business Services, Government Services and Personal Services). The series are for 11 countries in Africa, 11 countries in Asia, 2 countries in the Middle East and North Africa, and 9 in Latin-America. Data for the US and several European countries are also available. Value added data are expressed in local currencies. The data span the period 1948–2012 but the sample period depends on the specific country and series. We only consider the periods for which the employment data is available. Overall, almost all of the countries are in our sample in the period 1960–2010. Table 24 summarizes the countries and the sample periods used in our analysis.
World Income Inequality Database: it is collected by UNU–WIDER and provides several measures of income inequality for both developed and developing countries. In addition to the Gini coefficient and quintile and decile shares, survey means and medians along with the income shares of the richest 5% and the poorest 5% are also available.

Table 24. GGDC 10–Sector Database. Countries and Sample Periods.

Sub–Saharan Africa		Asia	
Country	**Sample Period**	**Country**	**Sample Period**
Botswana	1964–2010	China	1952–2011
Ethiopia	1961–2010	Hong Kong	1974–2011
Ghana	1960–2010	India	1960–2010
Kenya	1969–2010	Indonesia	1961–2012
Malawi	1966–2010	Japan	1953–2012
Mauritius	1970–2010	Korea	1963–2011
Nigeria	1960–2011	Malaysia	1975–2011
Ghana	1960–2010	Philippines	1971–2012
Senegal	1970–2010	Singapore	1970–2011
South Africa	1960–2010	Taiwan	1963–2012
Tanzania	1960–2010	Thailand	1960–2011

Latin America		Europe	
Country	**Sample Period**	**Country**	**Sample Period**
Argentina	1950–2011	Germany	1950–1991
Bolivia	1950–2010	Denmark	1948–2011
Brazil	1950–2011	Spain	1950–2011
Chile	1950–2012	France	1950–2011
Colombia	1950–2010	United Kingdom	1948–2011
Costa Rica	1950–2011	Italy	1951–2011
Mexico	1950–2012	Netherlands	1950–2011
Peru	1960–2011	Sweden	1950–2011
Venezuela	1950–2011		

North Africa		North America	
Country	**Sample Period**	**Country**	**Sample Period**
Egypt	1960–2012	United States	1950–2010
Morocco	1960–2012		

Appendix B - Additional Material

On TFP differentials as a source of Structural Change

In this section we explore whether existing theories of supply-driven structural change –that rely on productivity differentials across sectors in order to explain the reallocation of labor– can account for the observed patterns. In particular, Ngai and Pissarides (2007) postulate a theory according to which, under an elasticity of substitution smaller than 1, labor should flow into the sector that experiences the smallest TFP growth. In order to test this theory, we construct measures of sectoral TFP exploiting data on value added and employment at a disaggregated level[16]. Abstracting from capital as a production factor and assuming a production function linear in labor, TFP is accordingly defined as output per labor unit (as shown in Equation 45).

$$Y_{j,t} = A_{j,t} L_{j,t} \qquad \Longrightarrow \; A_{j,t} = \frac{Y_{j,t}}{L_{j,t}} \tag{45}$$

where $Y_{j,t}$ and $L_{j,t}$ are respectively value added produced and employed labor force in sector j at time t. Defining $\hat{X}_t$ as the growth rate of variable X at time t, the theory in Ngai and Pissarides (2007) implies the following relationship:

$$\hat{L}_{j,t} - \hat{L}_{i,t} = (1-\epsilon)(\hat{A}_{i,t} - \hat{A}_{j,t}) \tag{46}$$

where ϵ is the elasticity of substitution between goods, which is assumed to be constant. The consensus in the empirical literature is that $\epsilon < 1$, therefore implying a negative relationship between (relatively larger) TFP growth and (relatively larger) labor inflow[17]. When we have more than 2 sectors, very similar relationships apply: those sectors experiencing a larger (than average) TFP growth are the ones shrinking in terms of employment shares. In order to test these predictions, we first compute the sectoral TFP growth[18], then we aggregate it into the average TFP growth and eventually we compute the difference between the two growth rates. This difference should negatively correlate with the labor inflow. Surprisingly, Figure 16 shows that the reallocation of labor across sectors does not strictly follow productivity dynamics as implied by Ngai and Pissarides[19]. Even though the sign of the correlation in most of the cases tends to be negative as suggested by the theory, coefficients are very small and often not statistically significant. Moreover, the large dispersion of the observations in the scatter plots means that a supply-driven theory of structural change would fall short at accounting for the patterns observed in the data. This suggests that when accounting for structural change, at least part of the dynamics is explained by changes in the demand.

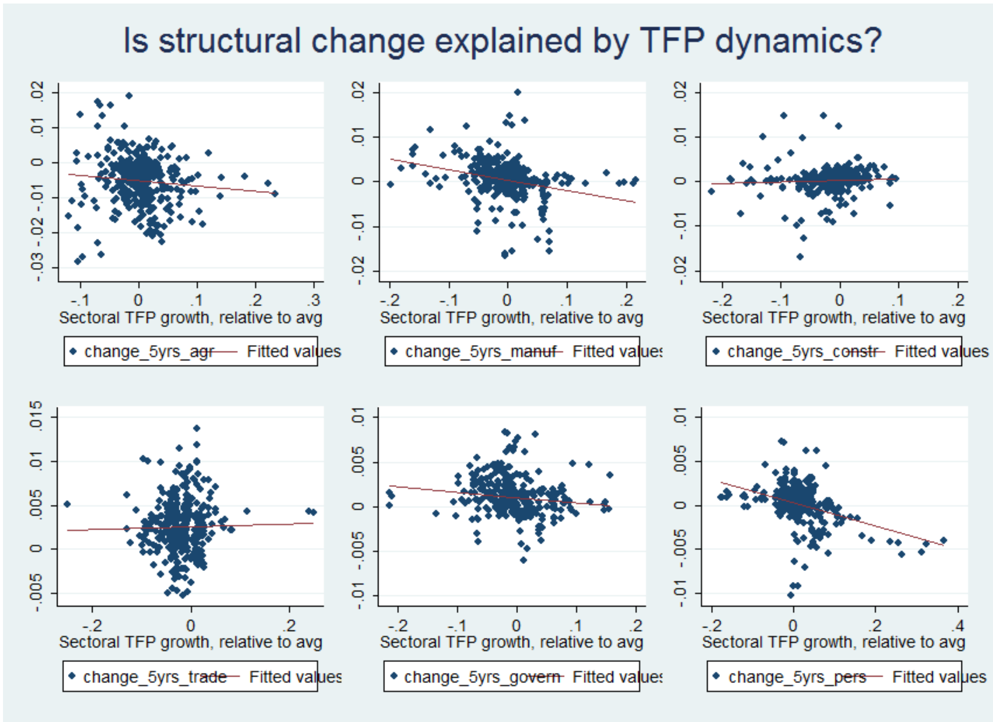

Figure 16. The vertical axis measures the net inflow/outflow from a given sector. The horizontal axis measures the sectoral TFP growth, relative to the average one, lagged 5 years. Observations are 5-year averages. The sectors are, respectively: Agriculture, Manufacturing, Construction, Trade Services, Government Services, Personal Services. (Source: Penn World Tables, 10SD).

Dependent Variable: Log GDP per capita

	(1) All Sample	(2) Top 50%	(3) Bottom 50%	(4) Bottom 33%	(5) Middle	(6) Top 33%
Agr. Emp. Share	-3.190***	-2.312***	-5.218***	-2.331***	-2.731***	-5.417***
	(0.060)	(0.063)	(0.080)	(0.070)	(0.106)	(0.095)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1583	970	613	711	491	381
R^2	0.648	0.590	0.877	0.615	0.579	0.898
Number of Countries	36	19	17	14	10	12

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 25. Linear Regression of log GDP per capita against agriculture employment share. The coefficient is estimated separately for the whole sample (column 1) and for different parts of the distribution of countries by income inequality in the period 1970-2010 (columns 2 to 6). Only observations with agriculture employment share of at least 0.1 are kept in the sample.

	Dependent Variable: Log GDP per capita			
	(1)	(2)	(3)	(4)
Agr. Emp. Share	-5.419***	-4.325***	-3.571***	-4.288***
	(0.079)	(0.110)	(0.099)	(0.117)
Agr. Emp. Share*High–Inequality	3.068***	2.895***	2.160***	2.724***
	(0.102)	(0.098)	(0.100)	(0.119)
Country FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes
Other controls	No	No	Yes	Yes
Controls for Nat. Resources	No	No	Yes	Yes
N	2099	2099	2099	1507
R^2	0.747	0.776	0.849	0.820
Number of Countries	41	41	41	39

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 26. Estimated coefficients for agriculture employment share and interaction term with high–inequality dummy (being in the top 50%). Controls include size of the country (total population), degree of openness, composition of GDP (consumption, investment and public expenditure), dependence on natural resources.

Other Material

Appendix B - Proofs

Lemma 2

The first statement follows from the fact that the willingness to pay for a given good j is strictly decreasing in j, together with the fact that technologies are the same across goods. To see this, take the derivative w.r.t. j of the LHS of Equation 3.4. Now, suppose that some good j is not consumed in equilibrium but instead some good j', with $j' > j$, is being consumed. The producer of j' is necessarily making non-negative profits, and would do so *a fortiori* for good j (for which the willingness to pay is higher). Then there is incentive for firms to produce and sell j.

The second statement follows from the fact that the willingness to pay for each given good j is increasing in the income level. To prove it formally, assume that we are in BGP and suppose that $N_R \leq N_P$. Then, it follows that $C_a^R > C_a^P$ must hold, the present value budget constraint of rich households would not be satisfied. From these two inequalities it follows that $\frac{C_a^R}{N_R} > \frac{C_a^P}{N_P}$. Now, evaluate equation 3.4 for both types of households for $j = N_P$. For the poor, it must be that the LHS is larger or equal to the RHS. Instead, for the rich it must be that the LHS is strictly smaller than the RHS. Taking the ratio between equation 3.3 and equation 3.4 for each type of household, you get the following two inequalities:

[16] The 10-Sector Database allows us to have data on 10 sectors of the economy: Agriculture, Mining, Manufacturing, Utilities, Construction, Trade Services, Business Services, Government Services and Personal Services.

[17] Assuming a stationary population, these relationships apply also in relative terms (employment shares).

[18] We use 5-year windows.

[19] We only report the figures for a selection of sectors (all the others feature very similar dynamics), for all countries. We have also investigated this relationship separately for high–inequality and low–inequality countries, and similar conclusions can be drawn for both samples. Observations are 5-year averages, consistently with the long-run horizon of structural change phenomenon.

Table 27. Movements of Labor across the 10 Sectors. Cumulative total outflow, total inflow and net inflow by sector and by Income Inequality group. Results are in percentage points of total employment.

Sector	Statistics	High Inequality	Low Inequality
Agriculture	Tot. Outflow	-38.30	-35.98
	Tot. Inflow	9.30	8.94
	Net Inflow	-29.01	-27.04
Mining	Tot. Outflow	-3.06	-1.63
	Tot. Inflow	2.35	0.83
	Net Inflow	-0.71	-0.81
Manufacturing	Tot. Outflow	-11.22	-14.33
	Tot. Inflow	11.13	11.55
	Net Inflow	-0.09	-2.78
Utilities	Tot. Outflow	-1.07	-0.65
	Tot. Inflow	1.16	0.68
	Net Inflow	0.09	0.03
Construction	Tot. Outflow	-7.30	-5.65
	Tot. Inflow	10.61	7.89
	Net Inflow	3.31	2.23
Trade Services	Tot. Outflow	-6.53	-4.28
	Tot. Inflow	18.54	12.11
	Net Inflow	12.00	7.83
Transport Services	Tot. Outflow	-3.00	-2.59
	Tot. Inflow	5.69	3.48
	Net Inflow	2.70	0.88
Business Services	Tot. Outflow	-2.07	-1.05
	Tot. Inflow	7.54	8.86
	Net Inflow	5.47	7.81
Government Services	Tot. Outflow	-3.07	-4.86
	Tot. Inflow	7.05	13.07
	Net Inflow	3.98	8.20
Personal Services	Tot. Outflow	-8.83	-2.72
	Tot. Inflow	11.09	6.14
	Net Inflow	2.26	3.42
All Services	Tot. Outflow	-4.29	-3.86
	Tot. Inflow	21.69	29.01
	Net Inflow	17.40	25.16

Lemma 3

Suppose not. Then there exists at least one good j such that $Y_j^O > 0$ and $Y_j^N > 0$. As implied by the FOC, under free competition $P_j^O = \frac{\psi^O}{\chi}$. Let us now consider P_j^N: it cannot be higher than P_j^O, otherwise the monopolist would attract no demand; it cannot be lower than P_j^O, otherwise nobody would buy from the competitive fringe. The only possibility is that $P_j^O = P_j^N$. But in such a case, the monopolist would have an incentive to cut the price by ϵ and get the whole market. We conclude that this cannot be an equilibrium.

$$\frac{\alpha}{1-\alpha}\frac{1}{1-\gamma}\frac{N_P(t)}{C_a^P(t)} \leq \frac{1}{P_{N_P}(t)} \tag{47}$$

$$\frac{\alpha}{1-\alpha}\frac{1}{1-\gamma}\frac{N_R(t)}{C_a^R(t)} > \frac{1}{P_{N_P}(t)} \tag{48}$$

Table 28. Average Yearly Labor Productivity Growth for the 10 Sectors, by Inequality Group.

Sector	High-Inequality	Low-Inequality
Agriculture	1.62	3.55
Mining	2.06	2.92
Manufacturing	1.88	3.52
Utilities	3.22	4.37
Construction	-0.05	1.49
Trade Services	-0.27	1.93
Transport Services	1.69	3.46
Business Services	0.97	2.08
Government Services	0.25	1.61
Personal Services	1.09	1.58
All Services	0.47	1.74

Combining equation 47 and equation 48, we get:

$$\frac{C_a^P(t)}{N_P(t)} \geq \frac{C_a^R(t)}{N_R(t)} \tag{49}$$

which implies that $\frac{C_a^P}{N_P} \geq \frac{C_a^R}{N_R}$. This is in contradiction with $\frac{C_a^R}{N_R} > \frac{C_a^P}{N_P}$, which was stated above. Hence, it must be the case that $N_P < N_R$ in a BGP. Now, given that both households face the same interest rate, the growth rate of N_P and N_R will be the same in equilibrium. This implies that also along the transition, $N_P(t) < N_R(t)$.

Equilibrium Characterization without Assumption U_C

We need to distinguish two cases here: $j^*(t) > N_P(t)$ (Case 1) and $j^*(t) \leq N_P(t)$ (Case 2). This is because only producers that have adopted the modern technology (monopolists) behave strategically when setting the price. Therefore, depending on whether monopolists have an incentive in cutting the price in order to enlarge their demand (that is, whether they are all selling to the whole market or not), equilibrium prices will be different.

Lemma 11 (Equilibrium Pricing). *Under Case 1 ($j^*(t) > N_P(t)$), equilibrium prices are as follows:*

$$P_j(t) = \begin{cases} \frac{\psi^O}{\chi} & \text{if } j \leq N_P(t)\left(\frac{P_{N_P(t)}}{\psi^O/\chi}\right)^{\frac{1}{\gamma}} \\ \left(\frac{N_P(t)}{j}\right)^{\gamma} P_{N_P}(t) & \text{if } N_P(t)\left(\frac{P_{N_P(t)}}{\psi^O/\chi}\right)^{\frac{1}{\gamma}} < j \leq N_P(t) \\ \frac{\psi^O}{\chi} & \text{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{50}$$

where $P_{N_P(t)} = [\pi\psi^O + (1-\pi)\psi^N]/\chi$.
Under Case 2 ($j^*(t) \leq N_P(t)$) equilibrium prices are flat: $P_j(t) = \frac{\psi^O}{\chi} \quad \forall j$.

Proof. **Case 1.** Under Case 1, a flat pricing profile cannot be an equilibrium. To see why, consider the producer of the good $N_P + \epsilon$, with ϵ small enough. By continuity of the willingness to pay of households, there exists a price cut ϵ_P small enough such that the producer of $N_P + \epsilon$ increases his profits by cutting his price to $\psi^O/\chi - \epsilon_P$ and discretely increasing the quantity sold from π to 1. In order to avoid this, in equilibrium the producer of N_P will set his price as to exactly make the producer of $N_P + \epsilon$ indifferent between his current profits and the ones he would obtain by cutting the price. : $1(P_{N_P(t)} - \psi^N/\chi) = \pi(\psi^O - \psi^N)/\chi$. Now consider the producers on the left of N_P. They are also threatened by the potential price cut of the producer of $N_P + \epsilon$. At the same time, they have the advantage that consumers strictly prefer their good relative to $N_P + \epsilon$. Making consumers indifferent between their goods and the good of the producer who can potentially cut the price (that is, equalizing the MRS to the relative

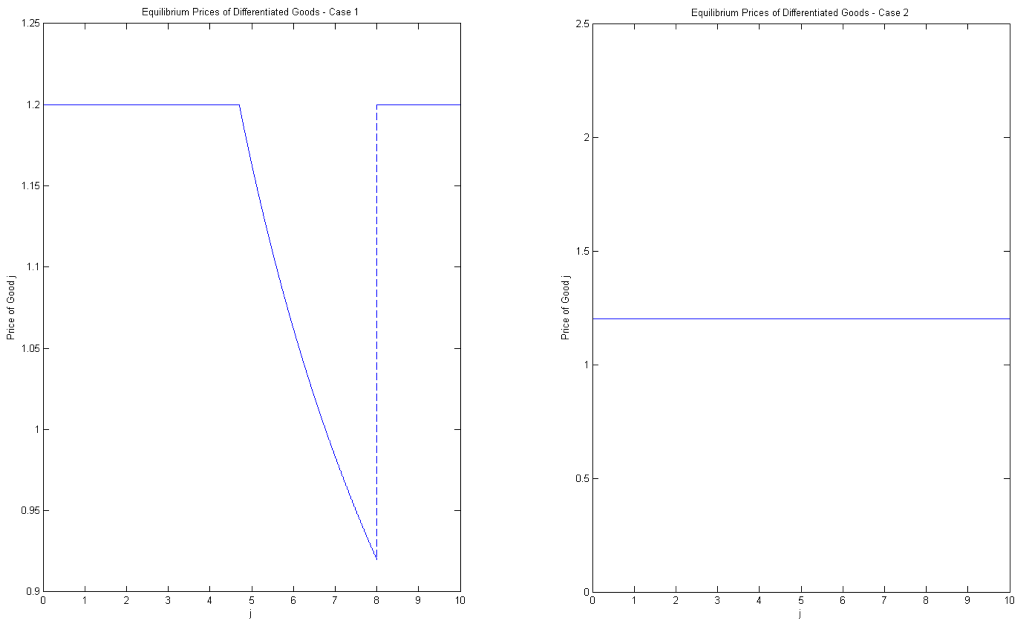

Figure 17. Equilibrium prices of differentiated goods. $N_P = 8$, $N_R = 10$, $\pi = 0.3$, $\psi^N = 0.8$, $\psi^O = 1.2$, $\chi = 1$, $\gamma = 0.5$.

price) yields the following: $P_j = (\frac{N_P}{j})^{\gamma} P_{N_P}$. Notice that according to this formula, $P_j \to \infty$ as $j \to 0$. At some point, for j small enough, this constraint will be less stringent than the threat of the competitive fringe. For this reason, for an interval of goods, the monopolist's price will be given by the limit price (same price that would be charged by the competitive fringe).

Case 2. Under Case 2, all monopolists are already maximizing the quantity sold. There have no incentive whatsoever to cut down the price, as they cannot attract additional consumers. At the same time, the competitive fringe is not fixing strategically the price. As a consequence, all monopolists will fix the price at the highest possible level. □

Under Case 1, the price is discontinuous at N_P, with a discrete jump in order to prevent competitors on the right of the hierarchy from cutting the price and attracting additional demand. On the left of N_P, there is an interval of producers who also have to adjust their price, in order to keep their customers. The more me move to the left, the more urgent the good becomes to the households and therefore producers can charge higher prices. In any case, the price cannot be higher than $\frac{\psi^O}{\chi}$, otherwise consumers would buy from the competitive fringe. Finally, prices on the right of N_P have to be equal to the maximum possible price, $\frac{\psi^O}{\chi}$, regardless of whether these goods are produced by a monopolist (until j^*) or by the competitive fringe (after j^*).

Under Case 2, instead, the pricing is simply flat, given that no monopolist has an incentive to reduce the price, as they are already selling to the entire population.

In the following, denote $\hat{j}(t) = N_P(t) \left(\frac{P_{N_P}(t)}{\psi^O/\chi} \right)^{\frac{1}{\gamma}}$. This is the last good for which the pricing is affected by potential price cuts of other producers. From the previous Lemma it follows that per-period operating profits are decreasing over j.

Corollary 12. *Under Case 1, profits have the following shape:*

$$
\Pi_j(t) = \begin{cases} \frac{\psi^O - \psi^N}{\chi} & \textit{if } j \leq \hat{j}(t) \\ \left[\left(\frac{N_P(t)}{j} \right)^{\gamma} P_{N_P}(t) - \frac{\psi^N}{\chi} \right] & \textit{if } \hat{j} < j \leq N_P \\ \frac{\psi^O - \psi^N}{\chi} \pi & \textit{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{51}
$$

Under Case 2 instead, profits are a step-function:

$$
\Pi_j(t) = \begin{cases} \frac{\psi^O - \psi^N}{\chi} & \textit{if } j \leq N_P \\ \frac{\psi^O - \psi^N}{\chi} \pi & \textit{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{52}
$$

Under Case 1, both the price and the quantity change over j. Let us look at N_P: for that good, the quantity has just discretely increased (from π to 1), while the price has dropped discontinuously. The price drop is such that it exactly offsets the increase in the quantity. From the point onwards, as we move to the left, the quantity stays constant but the price increases continuously, until $\hat{j}$.

Under Case 2, the price is always constant, and the only thing we notice is the *market size effect*, which discretely increases the profits at N_P.

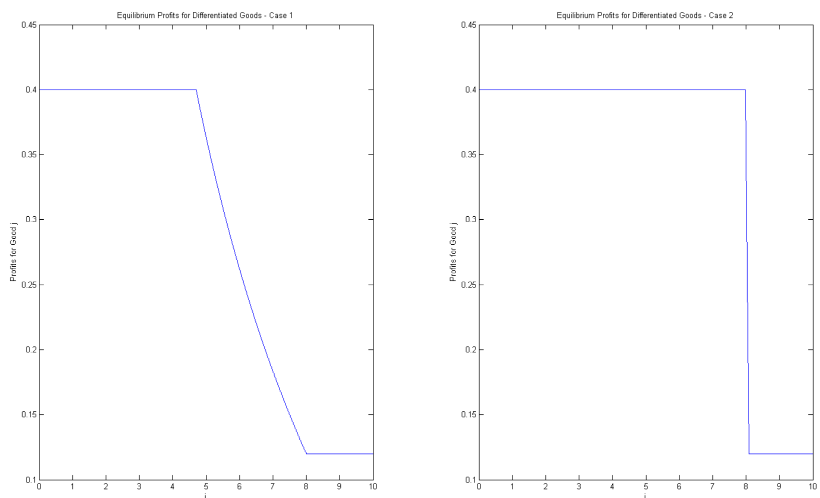

Figure 18. Equilibrium profits for differentiated goods. $N_P = 8$, $N_R = 10$, $\pi = 0.3$, $\psi^N = 0.8$, $\psi^O = 1.2$, $\chi = 1$, $\gamma = 0.5$.

Using equilibrium profits, we can write an expression for the value of innovation in each single good market. It corresponds to the infinite stream of discounted profits accruing from the technological adoption. The expression for $V_j(t)$ reads as follows:

$$
V_j(t) = \begin{cases} \frac{\psi^O - \psi^N}{\chi} \int_t^{\infty} e^{-R(s,t)} ds & \text{if } j \leq \hat{j}(t) \\ \int_t^{\infty} \left(P_j(s) - \frac{\psi^N}{\chi} \right) e^{-R(s,t)} ds & \text{if } \hat{j}(t) < j \leq N_P(t) \\ \int_t^{t+\Delta_j^M(t)} \left(\frac{\psi^O - \psi^N}{\chi} \pi \right) e^{-R(s,t)} ds + \int_{t+\Delta_j^M(t)}^{\infty} \left((P_j(s) - \frac{\psi^N}{\chi}) \right) e^{-R(s,t)} ds & \text{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{53}
$$

where $\Delta_j^M(t)$ is the waiting time for market j to become a mass market. That is, $N_P(t + \Delta_j^M(t)) = j$.
Notice that under Case 2, the expression for $V_j(t)$ simplify to the following:

$$V_j(t) = \begin{cases} \frac{\psi^O - \psi^N}{\chi} \int_t^\infty e^{-R(s,t)} ds & \text{if } j \leq N_P(t) \\ \frac{\psi^O - \psi^N}{\chi} \left[\int_t^{t+\Delta_j^M(t)} \pi e^{-R(s,t)} ds + \int_{t+\Delta_j^M(t)}^\infty e^{-R(s,t)} ds \right] & \text{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{54}$$

Lemma 13. *Innovation Values $V_j(t)$ is a continuous and decreasing function of j, $\forall t$. The unique equilibrium in which $\exists\, j \mid Y_j^O > 0$ and $\exists\, j' \mid Y_j'^N > 0$ (there is neither no adoption nor full adoption of modern technologies) must be such that $j^* \geq N_P$ (Case 1 or a knife-edge condition of Case 2).*

Proof. The continuity and monotonicity will be proven for Equation 53, as Equation 56 can be seen as a specific case of the former. Trivially, the function is constant in j in the first interval. Moreover, notice that as $j \to \hat{j}$, $P_j(s) \to \psi^O/\chi$. Therefore, the function is continuous at $j = \hat{j}$. Finally, notice that as $j \to N_P$, $\Delta_j^M \to 0$. This proves the continuity of the function. The monotonicity follows from the following. In the first interval, the function is constant and therefore monotonic. In the second interval, the price is a strictly decreasing function of j, as it follows from the equilibrium pricing. Last, in the third interval, price, quantity and Δ_j^M are changing over j. $\Delta_j^M \to 0$ as $j \to N_P$ from the right. This implies that more and more weight is given to the second integral, rather than the first one. Notice that the argument of the second integral (profits arising from selling to a mass market) is always larger than the argument of the first integral, as Corollary 12 shows. Therefore, the value of innovation is strictly decreasing in the third interval.
Technology Adoption Equilibrium: under Case 2, given the shape of the value of innovation, the only equilibrium is such that $F = (\psi^O - \psi^N)/\chi \int_t^\infty e^{-R(s,t)} ds$, and in that case $j^* = N_P$. Instead, under Case 1, the interval of possible equilibria is the following: $j^* \in (N_P, N_R]$. Given that $V_j(t)$ is strictly decreasing in that region and the fixed cost of adoption is a constant, the equilibrium must be unique. □

Lemma 14 (Optimal Consumption of Differentiated Goods)**.** *In equilibrium, Equation 3.4 must hold with equality for both types of households.*

Proof. Consider rich households, first. The pricing function for the last goods they consume is flat. That is, an additional good could be produced and sold at ψ^O/χ. If the consumption choice is optimal, it must be the case that they value the additional good less than ψ^O/χ. Given that the willingness to pay decays in a continuous fashion over j, then for the last consumed j the FOC must hold with equality.
Now turn to poor households. If we are in Case 2, the same argument as for the rich applies. Instead, if we are in Case 1, the willingness to pay for good N_P cannot be higher than ψ^O/χ, otherwise the poor would just consume more varieties. Similarly, it cannot be higher than P_{N_P}, otherwise there would be incentives for the producer of $N_P + \epsilon$ (for ϵ small enough) to cut his price. At the same time, it cannot be lower than P_{N_P}, as long as households are optimizing their consumption choice. We conclude that it must be equal to P_{N_P}. □

Balanced Growth Path

The rest of the analysis focuses on a Balanced Growth Path equilibrium, in which all variables grow at a constant rate. From equation 3.22 it is clear that when the consumption growth rate is constant ($g_c(t) = g_c \,\forall\, t$), the interest rate will also be constant: $r(t) = r \,\forall\, t$.
In a balanced growth path, the value of technological adoptions has a closed form. First, notice that in such a path it is possible to solve exlicitely for the waiting time $\Delta_j^M(t)$. $N_P(t) e^{g_c \Delta_j^M(t)} = j$ implies that $\Delta_j^M(t) = \frac{\log\left(\frac{j}{N_P(t)}\right)}{g_c}$, where g_c is the constant growth rate of N_P. The waiting time is increasing in the distance between N_P (the frontier of mass goods) and j, and decreasing in the rate of growth of such frontier. Second, substituting the fixed interest rate into equation 53, and plugging in the expression for the equilibrium prices from equation 50, it is now possible to solve the

integrals. Notice that in the interval $j \in [\hat{j}(t), N_P(t)]$, the price of good j starts at the level $\left(\frac{N_P(t)}{j}\right)^{\gamma} P_{N_P}$ and then grows at the constant rate $g\gamma$, until $\hat{j}$ reaches j. At that point, the producer is not constrained by the competition of the other monopolists anymore and can charge the maximum price (ψ^O/χ). In order to compute the infinite stream of profits, we first need to define the waiting time for a good (that is already a mass good) to be sold at the highest price. Let us define $\Delta_j^C(t)$ as the time that has to elapse from time t for good j to be sold at the highest price. It is defined such that $\hat{j}(t + \Delta_j^C(t)) = j$. Given that $\hat{j}$ grows at the constant rate g, we can solve for the waiting time: $\Delta_j^C(t) = \frac{\log\left(\frac{j}{\hat{j}(t)}\right)}{g}$.

Technological adoption has the following value, under Case 1:

$$V_j(t) = \begin{cases} \frac{\psi^O - \psi^N}{\chi} \frac{1}{r} & \text{if } j \leq \hat{j}(t) \\ \frac{e^{-r\Delta_j^C(t) + g\gamma\Delta_j^C(t)} - 1}{g\gamma - r} \left[P_{N_P} \left(\frac{N_P(t)}{j}\right)^{\gamma}\right] + \frac{e^{-r\Delta_j^C(t)} - 1}{-r} \frac{-\psi^N}{\chi} + \frac{e^{-r\Delta_j^C(t)}}{r} \frac{\psi^O - \psi^N}{\chi} & \text{if } \hat{j}(t) < j \leq N_P(t) \\ \frac{e^{-r\Delta_j^M(t)} - 1}{-r} \left(\frac{\psi^O - \psi^N}{\chi}\right) \pi + \frac{e^{-r(\Delta_j^M(t) + \Delta_j^C(t)) + g\gamma\Delta_j^C(t)} - e^{-r\Delta_j^M(t)}}{g\gamma - r} (P_{N_P}) + & \\ + \frac{e^{-r(\Delta_j^M(t) + \Delta_j^C(t))} - e^{-r\Delta_j^M(t)}}{-r} \left(\frac{-\psi^N}{\chi}\right) + \frac{e^{-r(\Delta_j^M(t) + \Delta_j^C(t))}}{r} \left(\frac{\psi^O - \psi^N}{\chi}\right) & \text{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{55}$$

In the interval $[0, \hat{j}]$, technological adoption yields lifetime profits from a market of size 1, selling at the highest price. Between $\hat{j}$ and N_P, the value of technological adoption corresponds to the profits coming from selling to a market of size 1, at a price that is changing over time for a period of time equal to $\Delta_j^C(t)$ (the first term), after which the price stays constant at the high level. Finally, technological adoption in the interval $[N_P, N_R]$ yields profits coming from selling to a market of size π for a period of time equal to $\Delta_j^M(t)$ (the first term), after which the quantity sold jumps to 1 and the price suddenly drops, starting to increase thereafter. After some time $\Delta_j^C(t) + \Delta_j^M(t)$, the price will have reached the highest level (last term). Notice that marginal costs are always constant and equal to $\frac{\psi^N}{\chi}$.

Instead, under Case 2, the expression simplifies further to:

$$V_j(t) = \begin{cases} \frac{\psi^O - \psi^N}{\chi} \frac{1}{r} & \text{if } j \leq N_P(t) \\ \frac{\psi^O - \psi^N}{\chi} \left(\pi \frac{1 - e^{-r\Delta_j^M(t)}}{r} + \frac{e^{-r\Delta_j^M(t)}}{r}\right) & \text{if } N_P(t) < j \leq N_R(t) \end{cases} \tag{56}$$

As it is clear, there is no change in price in this case. The quantity sold starts at π, for those goods between N_P and N_R, and then jumps to 1 after a period of time $\Delta_j^M(t)$.

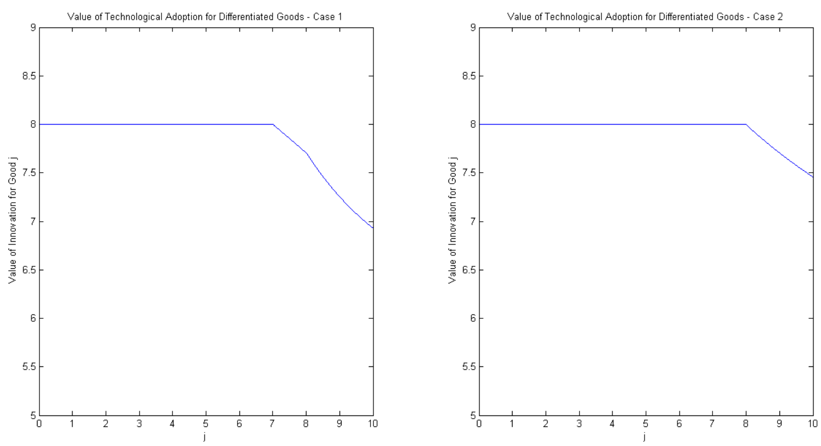

Figure 19. Value of Technological Adoption for differentiated goods. $N_P = 8$, $N_R = 10$, $\pi = 0.3$, $\psi^N = 0.8$, $\psi^O = 1.2$, $\chi = 1$, $\gamma = 0.5$, $r = 0.05$, $g_c = 0.11$.